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EDITORIAL

Agricultural extension is undergoing a profound transformation as global food systems confront the intertwined challenges of climate change, resource degradation, food and nutritional insecurity, and rapid technological advancement. Across the world, extension systems are evolving from conventional technology transfer models to innovation-driven, farmer-centric approaches that integrate artificial intelligence, digital platforms, climate services, precision agriculture, and data-informed decision-making. International initiatives emphasizing sustainable food systems, climate resilience, and digital public infrastructure have further reinforced the strategic role of extension in achieving the Sustainable Development Goals.

In India, these global developments coincide with an expanding digital agriculture ecosystem, increasing emphasis on climate-resilient farming, and renewed focus on entrepreneurship, value chains, and farmer producer organizations. While digital technologies offer unprecedented opportunities for personalized and timely advisory services, they also underscore the need to bridge digital divides, safeguard data privacy, and ensure that women, smallholders, tribal communities, and rural youth benefit equitably from emerging innovations. The future of extension therefore lies not in replacing human expertise with technology, but in strengthening extension professionals as facilitators of knowledge, innovation, and inclusive rural transformation. The Indian Council of Agricultural Research (ICAR) launched an Intensive Campaign on the Balanced Use of Fertilizers in May 2026 across high fertilizer-consuming districts to promote soil test-based nutrient management and the judicious application of fertilizers. Building on this initiative, the Government of India launched the Khet Bachao Abhiyan in June 2026, a nationwide campaign aimed at protecting agricultural land, restoring soil health, and promoting scientific and sustainable farming practices. Further strengthening the agricultural extension system, a Model Krishi Vigyan Kendra (KVK) is being established in Vidisha district, Madhya Pradesh, to serve as a “Live Laboratory” and a Centre of Excellence for demonstrating innovative technologies, advancing scientific farming, and fostering farmer-centric learning and capacity building.

The *Indian Journal of Extension Education* remains committed to respond to the rapidly changing realities. We encourage interdisciplinary research, methodological innovations, and evidence-based policy analyses that strengthen extension systems at local, national, and global levels. By fostering dialogue across disciplines and geographies, the journal seeks to contribute to resilient, inclusive, and sustainable agricultural development in an increasingly interconnected world. Present issue (July-September, 2026) features 52 manuscripts, including four research tools, eight research notes, and forty full-length papers, with double digit international contributions from Nepal, Iraq, Nigeria, Indonesia, and Vietnam. The papers covered a wide spectrum of contemporary issues in agricultural extension and rural development. Major themes included -Agricultural Extension, Communication and ICT; Artificial Intelligence, Machine Learning and Bibliometric Studies; Climate Change, Sustainability and Natural Resource Management; Entrepreneurship, Agripreneurship and Youth Aspirations; Technology Adoption, Knowledge and Farmer Behaviour; Gender, Social Inclusion and Rural Livelihoods; Indigenous Knowledge, Tribal Development and Rural Communities; Farmer Motivation, Livelihoods and Agricultural Economics; and Tourism and Rural Development. The collection reflects the growing emphasis on integrating digital technologies, sustainability, and socio-economic dimensions to strengthen agricultural extension and rural transformation.

On the basis of 333 included documents during 2022-25, the Scopus issued a Cite Score of 2.2 for 2025, SJR 0.293 and SNIP 0.546, however, as on date, Cite Score is 2.6 with 400 documents in Scopus database (*https://www.scopus.com/sourceid/21100846015)*. To give proper credit to the reviewers, from present issue, we have started publishing reviewers’ names on the manuscript itself.

On behalf of the editorial board, I extend sincere thanks to all reviewers, contributors, and members of the editorial and executive bodies for their continued support. We also acknowledge the publisher for maintaining timelines. Special appreciation is extended to Dr. U.S. Gautam, Dr. J.R. Mishra, Dr. Keshava, Dr. Basvaprabhu Jirli, and Dr. Bhanu P. Mishra for their valuable guidance.



(Manjeet Singh Nain)
Chief Editor

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Research Article

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Perceptions of Agricultural University Students toward the Use of ICT in Assam: A Multi-dimensional Analysis

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HIGHLIGHTS

- B.Sc. (Agriculture) students in Kamrup district of Assam demonstrated a consistently positive perception toward ICT across all measured dimensions.
- The dimension of Future Prospects and Career Relevance of ICT showed the greatest mean score (25.00/30)
- Institutional Support for ICT obtained the lowest mean score (20.62/30), revealing persisting deficiencies in infrastructure and technical assistance within surveyed universities.
- Gender was the sole socio-personal variable that significantly influenced ICT perception ($F=11.01$, $p=0.001$, $\eta^2=0.058$), with female students recording higher perception scores than the male students
- A strong positive inter dimensional correlation was observed between Learning and Knowledge Development and Agricultural Curriculum Integration ($r=0.724$, $p<0.01$)

ARTICLE INFO

Keywords: Perception, University students, ICT, Agricultural education, Gender differences, Assam.

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ABSTRACT

The study examined the perceptions of agricultural university students toward the utilisation of ICT in Kamrup district of Assam. A multi-stage random sampling was followed to select 180 students enrolled in B.Sc. and M.Sc. Agriculture programmes at two purposively chosen universities. Data collection was performed by using a self-constructed, validated questionnaire (test-retest reliability r=0.812) structured around five dimensions and each dimension comprised six items rated on a five-point likert scale. Analytical tools included mean, standard deviation, skewness, kurtosis, pearson inter-dimensional correlation, eta-squared (η^2) and one-way ANOVA. Findings revealed a consistently positive orientation toward ICT across all dimensions (composite M=117.93). Future Prospects and Career Relevance of ICT secured the highest mean (25.00), whereas Institutional Support for ICT recorded the lowest (20.62), indicating infrastructural limitations. ANOVA identified gender as the only significant socio-personal determinant of ICT perception ($F=11.01$, $p=0.001$; $\eta^2=0.058$; Cohen's $d=0.49$), with female students achieving higher scores (M=121.40) than that of the male students (M=114.68). Significant positive inter-dimensional correlations further confirmed the integrative role of ICT within the agricultural curriculum. The study calls for targeted investment in policy initiatives in ICT infrastructure and promotes gender-responsive digital literacy programmes to improve equitable ICT engagement in agricultural higher education.

INTRODUCTION

The 21st century has witnessed an unprecedented digital transformation that has fundamentally altered the way knowledge is created, disseminated and utilized across societies. Information and Communication Technology (ICT) constitutes a broad technological platform that enable individuals to access, retrieve,

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transform, store, organise and present data and information (Gay & Blades, 2019). Over the past two decades, the pervasive diffusion of digital technologies has exerted an unprecedented influence on higher education systems, reshaping pedagogical paradigms and learner engagement patterns across the globe (Kozma & Vota, 2013; Dhillon, 2026). The systematic embedding of ICT in university curricula has transitioned from an optional supplement to an institutionalised expectation (Shahid et al., 2019). The adoption of computer based and internet mediated applications is progressively transforming teaching and learning, with students increasingly making effective use of digital platforms for learning and knowledge construction, collaborative inquiry and academic productivity (Liu et al., 2010). Mustafa et al. (2023) observed that the integration of digital and mass media technologies into the teaching learning process enhances opportunities for interaction, collaboration and active engagement among learners across different levels of education. More critically, Kozlova and Pikhart (2021) demonstrated that ICT tools grant students access to diverse learning resources and facilitate dynamic engagement with instructors through digital platforms. Fu (2013) and Henderson et al. (2017) further established that contextualised ICT integration fosters innovative instructional strategies and measurably improves educational effectiveness

ICT enriched learning environments demonstrably sharpen student's analytical competencies and deepen their comprehension of agricultural methodologies (Mittal & Mehar, 2016, Aker, 2011). Consequently, integrating ICT into agricultural curricula is considered essential for enabling graduates to acquire technological fluency demanded by contemporary, precision centred farming systems (Qiang et al., 2012, Mapiye et al., 2023, Singh et al., 2025). In the context of Assam, ICT adoption in higher education has significantly expanded, with universities and colleges progressively incorporating digital resources, campus networks and technology enabled learning environments. Studies have documented the deployment of projectors, online learning management systems and digital library platforms, which have enhanced scholarly access and instructional efficiency (Nath, 2017; Upadhyaya & Rimzim, 2025). However, significant structural challenges persist, due to limited ICT infrastructure, inconsistent and unstable internet access (Das, 2020).

Moreover, geographic disparities in access to digital devices and stable connectivity entrench digital divides, disproportionately affecting rural and semi urban university communities. Against this backdrop, examining student's perceptions of ICT is not merely an academic exercise but a prerequisite for evidence based policy formulation. Perception shapes the willingness to adopt technology, the regularity of its use, and ultimately the magnitude of its educational impact (Zhao et al., 2021).

ICT enriches the pedagogical process by making instruction more responsive, participatory and contextually relevant (Feng et al., 2025). Its application in higher education has showed positive relationships with academic achievement (Karamti, 2016; Mehmood et al., 2022). Most previous studies have examined ICT adoption among general university students, teachers or farmers. However, empirical evidence focusing specifically on agricultural university students in northeast India remains limited.

METHODOLOGY

This study was conducted in the purposively selected Kamrup district of Assam during the academic year 2025-26. A multi stage sampling technique was employed for the selection of respondents. In the first stage, two universities namely Assam Down Town University and Royal Global University offering B.Sc. (Agriculture) programmes were purposively selected. In the second stage, out of 197 enrolled B.Sc. (Agriculture) students of Assam Down Town University 120 were selected and similarly out of 75 enrolled B.Sc. (Agriculture) students in Royal Global University 60 were selected, yielding a total sample of 180 students (93 male; 87 female). Data were collected through a self-constructed questionnaire designed to assess the multi-dimensional ICT perceptions of agricultural university students. An initial pool of 42 items was developed and after expert evaluation and pilot testing 30 items distributed equally (six items each) across five theoretically grounded dimensions: (i) Institutional Support for ICT (ii) ICT Use in Academic Activities (iii) Impact of ICT on Learning and Knowledge Development (iv) ICT and Agricultural Curriculum Integration, and (v) Future Prospects and Career Relevance of ICT. Responses were recorded on a five point Likert scale anchored at 1 (Strongly Disagree) and 5 (Strongly Agree), yielding a theoretical dimensional range of 6-30 and a composite range of 30-150. Content validity was established through review by twenty five subject matter experts in agricultural education and educational technology; items failing to achieve an item content validity index (I-CVI) of $\geq$0.78 were revised. Reliability was assessed using the test-retest method on a sub sample of 30 students over a two week interval, yielding a Pearson correlation coefficient of 0.812 ($p<0.01$), confirming satisfactory temporal stability of the instrument.

The study examined six socio-personal variables like gender, family background, father's education, mother's education (categorised into seven levels), father's occupation and mother's occupation and dependent variable perception. Data were analysed using IBM SPSS Statistics 27.0. Descriptive statistics (mean, standard deviation, skewness, and kurtosis) characterised the distribution of ICT perception scores. One-way ANOVA tested mean differences in overall ICT perception across socio-personal categories. Effect size was quantified using eta-squared (η^2 = SS_between / SS_total) and Cohen's d (for gender comparison) to contextualise the practical significance of statistically significant differences. A significance threshold of $\alpha = 0.05$ was uniformly applied throughout.

RESULTS

Dimension wise perception towards ICT

Table 1 presents the descriptive statistics for the five dimensions of ICT perception. The overall composite mean of 117.93 (out of a maximum of 150) reflects a positive orientation toward ICT among agricultural students. All dimensions recorded mean scores well above the neutral midpoint of 18 (for a 6-item, 5-point scale), with Future Prospects and Career Relevance of ICT securing the highest mean (25.00) and Institutional Support for ICT the lowest (20.62). Negative skewness values across all dimensions (ranging from -0.062 to -0.760) confirm a consistent left-skewed

Table 1. Dimension-wise descriptive statistics of ICT perception (n=180; max score per dimension=30)

Dimension	N	Mean	Std. Dev.	Skewness	Kurtosis
Institutional Support for ICT	180	20.62	3.08	-0.062	0.383
ICT Use in Academic Activities	180	23.04	3.57	-0.181	-0.441
Impact of ICT on Learning and Knowledge Development	180	24.43	3.68	-0.352	-0.518
ICT and Agricultural Curriculum Integration	180	24.84	3.64	-0.684	-0.060
Future Prospects and Career Relevance of ICT	180	25.00	3.46	-0.760	-0.301
Composite Score (Total)	180	117.93	13.96	-0.606	-0.362

response pattern, indicating that respondents generally endorsed higher levels of agreement. The near-platykurtic kurtosis values for most dimensions suggest relatively flat, broadly distributed response profiles rather than sharply peaked concentration.

Gender wise comparison of ICT perception

Table 2 presents the gender-wise means and standard deviations for the five dimensions and the composite ICT perception score. Female students consistently reported higher mean scores across all dimensions, with the largest absolute gap observed in ICT Use in Academic Activities (Δ=1.56) and Future Prospects and Career Relevance (Δ=1.65). The composite score difference of 6.72 points is statistically significant (F=11.01, p=0.001), and the computed effect size (η^2=0.058; Cohen's d=0.49) indicates a medium practical effect. These findings suggest that female agricultural students, despite the broader societal narrative of differential technology access, demonstrate stronger positive perceptions and higher engagement with ICT in the academic context examined.

Inter dimensional correlation analysis

Table 3 present the Pearson inter-dimensional correlation matrix for the five ICT perception constructs. All correlation coefficients were positive and statistically significant ($p<0.05$), confirming the convergent validity of the instrument and the theoretical coherence of the ICT perception model. The strongest correlation was observed between Learning and Knowledge Development and Agricultural Curriculum Integration (r=0.724, $p<0.01$), pointing to the idea that students who regard ICT as enhancing their learning also tend to believe that it is well-integrated into their agricultural curriculum. Future Prospects and Career Relevance was most strongly correlated with Curriculum Integration (r=0.705, $p<0.01$) and Learning and Knowledge Development (r=0.652, $p<0.01$), reflecting the perceived career and educational value of curriculum-embedded digital practices. Institutional Support for ICT demonstrated the weakest correlations with other dimensions (r=0.352-0.524), consistent with the relatively lower mean scores on this dimension and suggesting that infrastructure-related perceptions form a somewhat independent sub-domain of overall ICT attitude. These inter-dimensional patterns highlight ICT perception as a multi-faceted but internally consistent construct.

ANOVA: Effect of socio-personal variables on ICT perception

Table 4 presents the results of the statistical analysis examining differences in composite ICT perception scores across selected socio-personal variables. Gender was assessed using an independent samples t-test, while variables comprising more than two categories were analysed using one way ANOVA. The result revealed a significant difference between male and female students with female students reporting more favourable perceptions towards ICT than

Table 2. Gender wise mean comparison of ICT perception scores across dimensions

Dimension	Male Mean (n=93)	Male SD	Female Mean (n=87)	Female SD	Mean Difference
Institutional Support for ICT	19.90	3.32	21.37	2.71	1.47
ICT Use in Academic Activities	22.30	3.84	23.86	3.24	1.56
Impact of ICT on Learning and Knowledge Development	23.90	3.88	25.01	3.40	1.11
ICT and Agricultural Curriculum Integration	24.40	3.82	25.33	3.38	0.93
Future Prospects and Career Relevance of ICT	24.18	3.62	25.83	3.18	1.65
Composite Score	114.68	14.89	121.40	12.05	6.72*

* Significant at $p<0.001$; F=11.01, df=1,178; η^2=0.058; Cohen's d=0.49 (medium effect)

Table 3. Inter-dimensional Pearson correlation matrix of ICT perception (n=180)

Dimension	IS	AA	LK	CI	FC
Institutional Support (IS)	1.000	0.524**	0.441**	0.383**	0.352*
Academic Activities (AA)	0.524**	1.000	0.683**	0.612**	0.578**
Learning & Knowledge Dev. (LK)	0.441**	0.683**	1.000	0.724**	0.652**
Curriculum Integration (CI)	0.383**	0.612**	0.724**	1.000	0.705**
Future Prospects (FC)	0.352*	0.578**	0.652**	0.705**	1.000

* $p<0.05$; ** $p<0.01$ (two-tailed). IS=Institutional Support; AA=Academic Activities; LK=Learning & Knowledge Development; CI=Curriculum Integration; FC=Future Prospects & Career Relevance

Table 4. Comparison of Composite ICT Perception Scores across Socio-personal Variables

Variable	Statistical Test	Test Statistic	p-value	Effect Size
Gender	Independent Samples t-test	t = 3.32	0.001**	Cohen's d = 0.49
Family Background	One-way ANOVA	F = 0.176	0.840	η^2 = 0.002
Father's Education	One-way ANOVA	F = 1.419	0.210	η^2 = 0.047
Mother's Education	One-way ANOVA	F = 2.120	0.053†	η^2 = 0.069
Father's Occupation	One-way ANOVA	F = 0.723	0.487	η^2 = 0.008
Mother's Occupation	One-way ANOVA	F = 0.825	0.440	η^2 = 0.009

Notes: η^2 = Eta-squared effect size. Cohen's d was calculated for gender comparison. ** *p<0.01*

their male counter parts (t=3.32, p= 0.001, Cohen's d= 0.49). The magnitude of the effect was moderate, indicating that gender contributed meaningfully to variations in ICT perception. No significant difference was observed with respect to family background, father's education, father's occupation, mother's occupation. Although mothers education did not reach the conventional level of statistical significance, the result approached significance (F=2.120, P=0.053) suggesting that maternal education attainment may warrant further investigation in future studies. The non-significance across parental educational and occupational categories suggests a degree of homogeneity in ICT exposure and attitudes within this student cohort, potentially attributable to the equalising effect of university-level digital exposure transcending home background differentials.

DISCUSSION

The overall positive orientation of agricultural students toward ICT (composite M=117.93/150) is consistent with the growing body of evidence documenting favourable technology attitudes among university cohorts in developing economies (Shanila & Helen, 2025). The consistently high mean scores across learning focused and curriculum related dimensions echo Aker (2011), who documented the transformative potential of ICT in democratising access to agricultural and educational information in regions where formal extension infrastructure remains limited. Similarly, Mittal and Mehar (2016) and Panda et al. (2019) reported that ICT tools substantially augmented knowledge transmission and analytical capacity among agricultural learners a pattern replicated in the present study, where the dimension of impact of ict on learning and knowledge development attained a mean of 24.43 reinforcing Fu's (2013) assertion that contextualised ICT integration fosters innovative instructional strategies and measurably improves educational outcomes. The highest ranked dimension i.e. future prospects and career relevance of ICT (M=25.00) corroborates the findings of Qiang et al. (2012), who demonstrated that digital tools directly expand professional opportunities and career readiness in developing countries, particularly for agriculture related occupations undergoing rapid technological transformation. The prominence of the future prospects and career relevance dimension may also reflect the ongoing digital transformation of agriculture. Technologies such as precision farming, remote sensing, geographic information systems, digital advisory services and artificial intelligence are increasingly shaping agricultural practice. Consequently, students may view ICT competence as a prerequisite for employability and professional success in the evolving agricultural sector. The alignment of these findings with Kozlova and Pikhart (2021) further supports the proposition that ICT augments the flexibility and diversity of learning resources available to students, thereby enhancing higher education systems adaptive capacity. The high scores recorded for learning enhancement, curriculum integration and career relevance indicate that agricultural students largely recognise the practical value of ICT in supporting both academic and professional development. Such perceptions are likely to encourage greater acceptance of digital technologies within agricultural education settings.

Conversely, Institutional Support for ICT yielded the lowest dimension mean (20.62). This finding is consistent with the infrastructural deficiencies documented by Das (2020) in North-East Indian universities and parallels the recurrent theme in ICT adoption literature that institutional and contextual constraints constitute a more significant barrier than individual attitudinal resistance. The study found gender significantly differentiated ICT perception (t= 3.32, p= 0.001) challenges the commonly held assumption that male students are more positively disposed toward technology. This is partly consistent with Claro et al. (2012), who found that gender based differences in ICT attitudes are mediated by contextual exposure and curricular engagement, rather than determined by fixed dispositional traits. The findings may also indicate changing patterns of digital participation among young women in higher education. Increasing access to digital devices, improved educational opportunities, and growing exposure to technology-enabled learning environments may be contributing to the narrowing of traditional gender gaps in ICT-related attitudes. Within agricultural education, ICT may additionally be perceived as a means of enhancing access to information, professional networking, and career opportunities. The lower standard deviation among female respondents may also indicate greater internal consistency in their ICT attitudes, possibly reflecting more uniform patterns of ICT use within the female student cohort (Paliwal et al., 2026). The consistency of higher perception scores among female students highlights the need for gender responsive digital literature initiatives that recognise and build upon the favourable attitudes towards ICT demonstrated by female agricultural students. However, present findings should be interpreted as reflecting perceptions rather than actual pattern of ICT utilization. However, the marginal significance of mother's education (p=0.053, η^2=0.069) merits further investigation: emerging evidence from comparable contexts indicates that maternal education and its associated digital socialisation practices exert a subtle influence on children's educational technology attitudes (Karamti, 2016; Mehmood et al.,

2022). The inter-dimensional correlation analysis revealed that impact of ICT on learning and knowledge development and agricultural curriculum integration shared the strongest positive relationship ($r=0.724$, $p<0.01$), confirming that curriculum embedded ICT use is perceived as a meaningful mechanism of knowledge construction rather than a superficial instructional add-on. The relatively weaker correlations involving Institutional Support ($r=0.352$-0.524) reinforce the interpretation that infrastructure related perceptions are somewhat detached from the experiential, learning oriented dimensions a pattern that may reflect students' capacity to derive educational value from ICT even in the presence of institutional shortcomings, leveraging personal devices and off-campus connectivity. This resilience is documented in the literature on mobile learning in resource constrained environments (Qiang et al., 2012; Sondarava et al., 2023; Sahoo et al., 2025).

On the basis of these findings, the study recommends; targeted investment in ICT infrastructure including reliable internet access, upgraded computer laboratories, and resident technical support teams - particularly in agriculture departments of universities in Assam; the design of gender-responsive digital literacy programmes that channel the stronger ICT engagement observed among female students into peer-learning and mentorship roles; structured curriculum reform that formally integrating ICT tools into agricultural course delivery, assessment, and field-based learning; and periodic perception audits using validated multi-dimensional instruments to track institutional progress in ICT adoption. These findings are of direct utility for agricultural education policymakers, institutional administrators, and curriculum designers committed to building digitally fluent, career ready graduates capable of navigating the technology intensive demands of modern agricultural science and practice.

CONCLUSION

Selected students exhibited a consistently positive and multi-dimensionally coherent perception toward ICT. The dimension of future prospects and career relevance of ICT attracted the highest endorsement. Agricultural curriculum integration and learning and knowledge development were comparably well regarded, underscoring ICT's perceived pedagogical centrality. The relatively lower mean for institutional support signals a persistent infrastructure gap, if unaddressed, risks limiting the conversion of positive ICT attitudes into consistent, high quality digital learning practices. Gender emerged as the sole statistically significant socio-personal differentiator of ICT perception, with female students demonstrating stronger positive attitudes. Inter dimensional correlation analysis confirmed the internal coherence and convergent validity of the five dimensional perception model, with particularly strong linkages between learning oriented and curriculum related constructs.

DECLARATION

Ethical approval and consent to participate: Our study did not require ethical approval and all the authors agree. However the informed consent was sought from the respondents.

Consent of publication: Participants provided consent for publication

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Research Article

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Global Knowledge Structure of Agricultural Entrepreneurship and Entrepreneurial Behaviour Research: A Bibliometric Analysis

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HIGHLIGHTS

- Progressive growth in publications on agricultural entrepreneurship was observed, particularly after 2010.
- Keyword network analysis identifies dominant themes, including entrepreneurship, innovation, sustainability, rural development, and farmer entrepreneurial behaviour in agricultural research.
- International collaboration analysis highlights major contributions from countries such as the United States, China, and India in agricultural entrepreneurship.

ARTICLE INFO

Keywords: Agricultural entrepreneurship, Entrepreneurial behaviour, Bibliometric analysis, Rural development, Innovation, Sustainability.

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ABSTRACT

The research was undertaken in the period 2024-2025 to discuss the research trends in the world, thematic development, and network of collaboration in agricultural entrepreneurship and entrepreneurial behaviour of farmers through a bibliometric analysis method. The database was gathered by using a large scientific database where a set of 710 research articles published in 2016-25 were located and assessed with the help of Biblioshiny and VOSviewer software. To comprehend the intellectual framework of the research area, the analysis was conducted on annual scientific production, collaboration networks between those who use the same keywords, collaboration between authors, and collaboration between countries. The findings depict that there was a vast increase in publications, and this growth rate is 17.05 per annum, signifying that the world's interest in agricultural entrepreneurship and entrepreneurial behaviour is growing. Network visualisation also evidences that the countries have very strong international connections, such as the United States, China, India, and a number of European countries. The results show that the studies in the field are progressively becoming more interdisciplinary and interconnected worldwide, with a focus on innovative, sustainable, and farmer-focused entrepreneurial growth.

INTRODUCTION

Agriculture is one of the essential sectors of economic growth, food security, and livelihood in the global context. In most developing nations, a big percentage of the population relies on farming as a major means of earning their living and also as an employment. However, the traditional agricultural systems are becoming challenged by the problems like climate change, reduction of productivity, unstable market and scarcity of resources. Agricultural entrepreneurship means the capabilities of farmers and agribusiness participants to see new opportunities, introduce new technologies, take risks, and generate value-added processes in the

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agricultural industry (Sirine et al., 2020). The emerging trend on entrepreneurship in agriculture is representative of a larger shift in the agricultural industry towards production based on subsistence to a more market-oriented and innovation-based production system (Licciardo et al., 2023). With the entrepreneurial farmers, there are increased chances of adopting better technologies, diversifying the farm activities, new markets, as well as involvement in the value chain development. This kind of entrepreneurial activity helps to enhance the agricultural productivity and the economic development in rural areas (Xie et al., 2021; Lu et al., 2025)).

The studies of the topic of agricultural entrepreneurship have gained momentum in recent years in spheres like agricultural economics, sociology of rural areas, developmental studies, and innovation management (Kademani et al., 2024). Researchers have paid more attention to the determinants of entrepreneurial behavior among the farmers, the institutional support and the influence of entrepreneurship on the rural development. Research has emphasized that entrepreneurship is important in enhancing the economic standing of rural areas and advancing innovation in the agricultural production systems, and the robustness of food systems (Malan, 2020; Scott & Richardson, 2021). Moreover, the idea of sustainable agricultural entrepreneurship has become popular as a strategy accomplishing both economic development and environmental sustainability and social welfare (Kurtaj et al., 2024).

The entrepreneurial orientation and access to information are the two factors that strongly determine how the farmers are able to adopt new technologies, manage their farms more efficiently, and respond to market opportunities (Selemani et al., 2025). Studies have indicated that there is a strong impact by the psychological, social, and economic factors on the entrepreneurial behavior of farmers and the decision-making process (Hu et al., 2021). Also, the formation of agricultural entrepreneurship is closely intertwined with the support of the policy, access to funds and training, and institutional structures that allow farmers to engage in the competitive markets (Van Niekerk et al., 2024). Although there has been an increased attention towards this area of study, there is still a fragmented scientific body in this area of research among various disciplines and geographical locations. Bibliometric analysis has become a potent instrument to study the intellectual organization of research disciplines in terms of patterns of publications, connections between keywords as well as networks between researchers and nations (Ghertescu et al., 2024).

Thus, the current research will focus on the bibliometric review of the international literature on agricultural entrepreneurship and entrepreneurial behaviour to determine the key research topics, partnerships, and new policies. Through the co-authorship network and key word co-occurrence patterns analysis, the research is able to present the knowledge structure of agricultural entrepreneurship research that is emerging. The results of this review will help to comprehend the research situation more properly and offer the path forward to the subsequent research, policy development, and stimulation of the entrepreneurial activity in agriculture.

METHODOLOGY

The study adopted a bibliometric methodology to examine global research trends, collaborative networks, and thematic structures in the field of agricultural entrepreneurship. Bibliometric analysis is widely used for the quantitative assessment of scientific literature and for identifying patterns of research development, collaboration, and knowledge structures within a given domain. The bibliographic data for this study were retrieved from the Scopus database, chosen for its comprehensive coverage of peer- reviewed journals. The data collection covered the period from 2016-2025 and was conducted using a clearly defined and reproducible search strategy. The search string applied was “agricultural entrepreneurship” or “agripreneurship” or “farm entrepreneurship” or “agribusiness entrepreneurship” and “rural development” or “sustainable agriculture” or “farming system”, using appropriate Boolean operators. Only peer- reviewed journal articles published in English and directly relevant to the study domain were included, while conference papers, book chapters, editorials, and duplicate or irrelevant records were excluded. A total of 710 records were retrieved and exported in CSV and bibliographic formats, containing detailed information such as tile, authors, publication year, affiliations, country, author keywords, index keywords, and references. The dataset was carefully cleaned and standardised to ensure consistency and reliability, including the removal of duplicate entries, normalisation of author names and affiliations, and harmonisation of similar keywords to improve the accuracy of network analysis. The cleaned data were then analyzed using Biblioshiny and VOSviewer, which are widely recognised tools in scientometric research. Specific parameters were applied to enhance transparency and reproducibility, including full counting methods, a minimum threshold of five documents per country for co-authorship analysis, and minimum keyword occurrence thresholds. Network normalisation was performed using the association strength method, and clustering was conducted using the VOS clustering algorithm. The analysis was carried out in three stages: first, country- level co-authorship analysis to identify international research collaborations, where countries were treated as nodes and links represented collaborative relationships; second, co-occurrence analysis of author keyword to identify major research themes and conceptual clusters; and third, index keyword analysis to further validate thematic relationships. VOSviewer was used to generate bibliometric maps based on co-occurrence and collaboration networks where node size indicated frequency or influence, links represented relationships, and different colours denoted thematic clusters. These visualisations enabled the identification of major research hubs, collaborative networks, and evolving thematic structures, thereby providing a comprehensive and reproducible understanding of the global research landscape in agricultural entrepreneurship.

RESULTS

A bibliometric overview created with the help of the Biblioshiny interface provides a summary of the dataset that is utilised to make the analysis of the research on agricultural entrepreneurship (Van Eck & Waltman, 2010; Roy et al., 2024). The data span is between 2016 and 2025, which is ten years of study and development in this field.

The sources used in retrieving 710 documents comprised 373 sources, meaning the research conducted in the field of agricultural

entrepreneurship has found publication in a vast scope of academic journals and publications. The review indicates that the growth rate was 17.05 per year which clearly shows that the amount of research output in the field has increased at a high rate over the period of study. The mean age of the documents is 4.28 years, indicating a majority of the literature is relatively young and adopts some of the new trends regarding agricultural entrepreneurship research. Concerning the citation impact, there is 70626 references in publications with the mean of citations of 13.71 per document thus indicating the considerable academic impact of the literature. There are also 1,168 Keywords Plus and 2,304 author keywords in the dataset which indicates the variety of the research topics discussed in the field. The authorship analysis shows that there are 2,247 authors of the 710 publications, 76 of which are single-authored, which implies that the majority of research in the given field is performed in teams. The mean size of co-authors is 3.49 and 22.11 per cent of the documents are international co-authored, which means that there is a high level of collaboration between scholars in the study of agricultural entrepreneurship.

Figure 1 shows the scientific output of the publications on agricultural entrepreneurship in 2016-2025. The findings reveal that there is a progressive growth in research output. In 2016, the number of publications was about 30-35 articles, but in 2025 it rose to over 130 publications.

The observed progressive growth in publications on agricultural entrepreneurship, particularly after 2010, reflects broader structural transformations in the global agricultural sector. This increase can be attributed to the rising recognition of entrepreneurship as a key mechanism for enhancing farm income, promoting rural employment, and addressing emphasis on sustainable development (FAO, 2017) especially following the adoption of the United Nations Sustainable Development Goals (SDGs) in 2015, which highlighted the role of innovation and entrepreneurship in achieving food security and rural sustainability (United Nations, 2015). Furthermore, thematic shifts identified through keyword analysis- such as the growing prominence of sustainability, innovation systems, and value chain development can be linked to increasing concerns over climate change, resource degradation, and market integration. The integration of concepts such as social capital and rural resilience suggests a transition from purely economic perspectives toward more holistic and system- based approaches in agricultural research (FAO, 2018; World Bank, 2020). These trends indicate that agricultural entrepreneurship research is not only expanding in volume but also evolving in response to global challenges, policy priorities, and technological advancements, thereby reflecting its increasing relevance in shaping sustainable and inclusive rural development pathways (Scoones, 2016; OECD, 2019).

There is a minor drop in the period of the year 2023 however the trend indicates strongly upwards. This is indicated by the increased number of publications since 2023 and indicates a worldly interest in the topic of agricultural entrepreneurship, especially regarding the new issues faced by the world (food security, rural unemployment, climate change, and sustainable agricultural development) (Mansingh et al., 2025; Kurtaj et al., 2025).

Three field- plot analysis Figure 2 demonstrates the three-field plot, which depicts the correlation between cited references (CR), authors (AU), and keywords (KW) in the agricultural entrepreneurship literature. The visualization indicates the intellectual relations between the authoritative sources, the references, and the prevailing topics in the research. It can be seen that such authors as Dentoni, Domenico; McElwee, Gerard; Gittins, Peter and Methorst, Ron are highly linked with references of power (Gittins and McElwee, 2023). The main related research topics of these authors include entrepreneurship, agriculture, rural economy, rural entrepreneurship, sustainability, innovation, and smallholder farming systems.

The Figure 2 in terms of the keyword dimension shows that entrepreneurship and entrepreneur are the most popular keywords, then there are agriculture, rural economy, rural entrepreneurship, smallholder, farmers, sustainability, rural development and innovation. These key words show that the research on agricultural entrepreneurship is mostly concerned with the enhancement of the rural economies and the national support of the sustainable farming systems by means of the entrepreneurial activity (Sirine et al., 2020; Kurtaj et al., 2024).

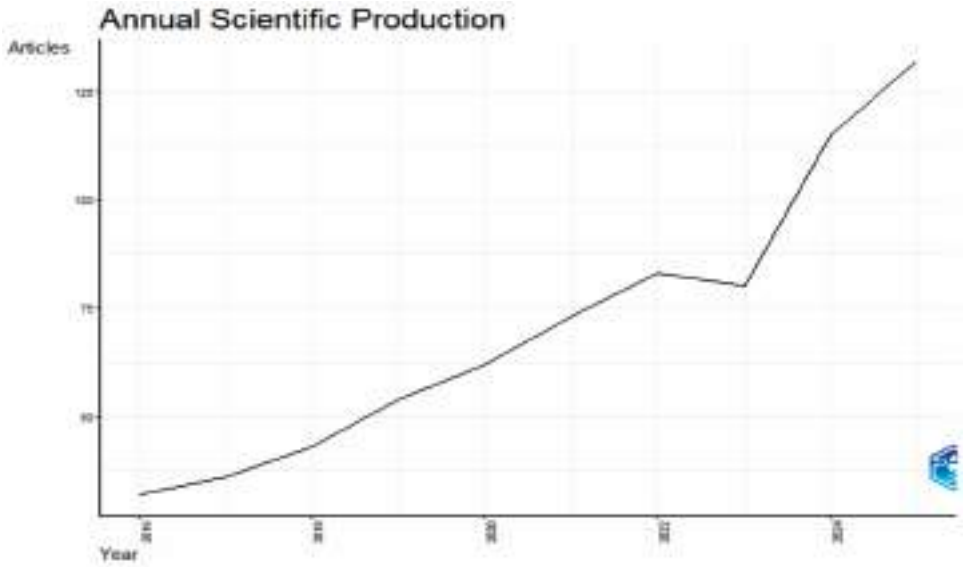


Figure 1. Annual Scientific Production in Agricultural Entrepreneurship Research (2016- 2025)

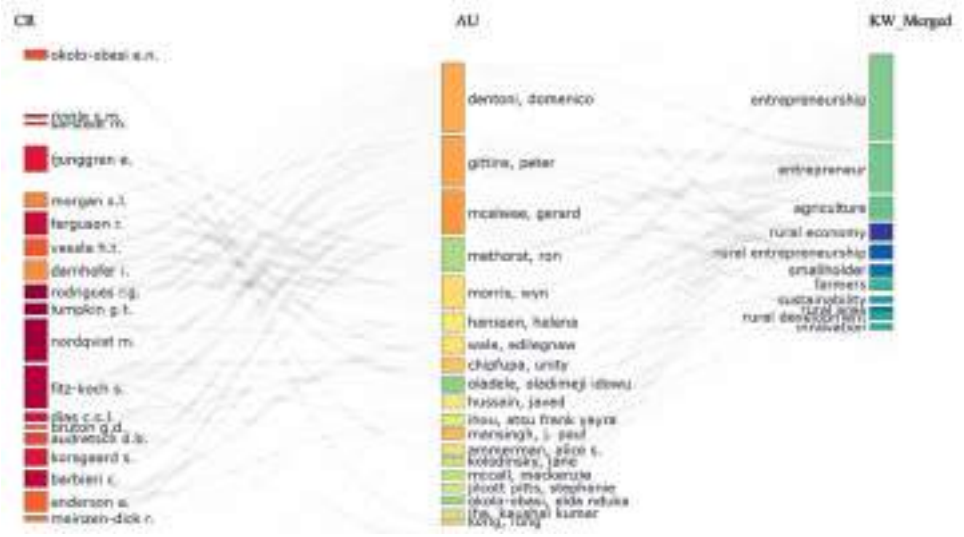


Figure 2. Three-field plot analysis showing the relationship among cited References, Authors and Keywords

The Biblioshiny analysis of the gathered data sheds light on the fast growth of studies in the area of the agricultural entrepreneurship throughout the world. The review shows that the academic contribution to the study has seen a sharp rise in the last twenty years, which is indicative of the recent scholarly interests in entrepreneurship, as a tool of agricultural transformation, rural development and livelihood enhancement. The bibliometric measures indicate that the research in agricultural entrepreneurship is very inter-disciplinary, which incorporates the input of agricultural economics, rural sociology, agribusiness management, innovation studies, and development economics.

Characteristics of the literature: It has a wide range of research themes such as entrepreneurial behavior (Anna et al., 2021) among farmers, agriculture innovation systems, sustainability transition, employment creation in the rural areas, and the development of the value chain. The analysis of the conceptual structure of Biblioshiny also shows that the study in the given area is closely connected with the issues of the innovation, rural economy, food security, social capital, and sustainable agricultural systems (Nguyen et al., 2025). These thematic areas reveal that the present condition of agricultural entrepreneurship is seen as not only a business but also a source of bigger rural changes. The bibliometric outcomes also indicate that the cooperation between the nations and institutions takes an important part in the development of the global research. Nations that have good agricultural research facilities and have aggressive rural development projects are likely to make more contributions to this area.

The unique selection of the keywords co-occurrence network created with the help of VOSviewer offers the hints at the conceptual framework of the agricultural entrepreneurship study. The visualization map depicts the correlation between common keywords within the author list whereby the size of the node represents the frequency of the keyword and the links are used to show the correlation between two concepts. The network visualization shows that there were a number of different thematic clusters of the various directions of research in the field.

The biggest and most central keyword of the network is entrepreneur, and it means that the entrepreneurial behavior and the entrepreneurship activity are the main focus of the research on the agricultural entrepreneurship. Sustainability, innovation, smallholder, and rural development are closely related words, and the relevance of entrepreneurship to restructure the systems of

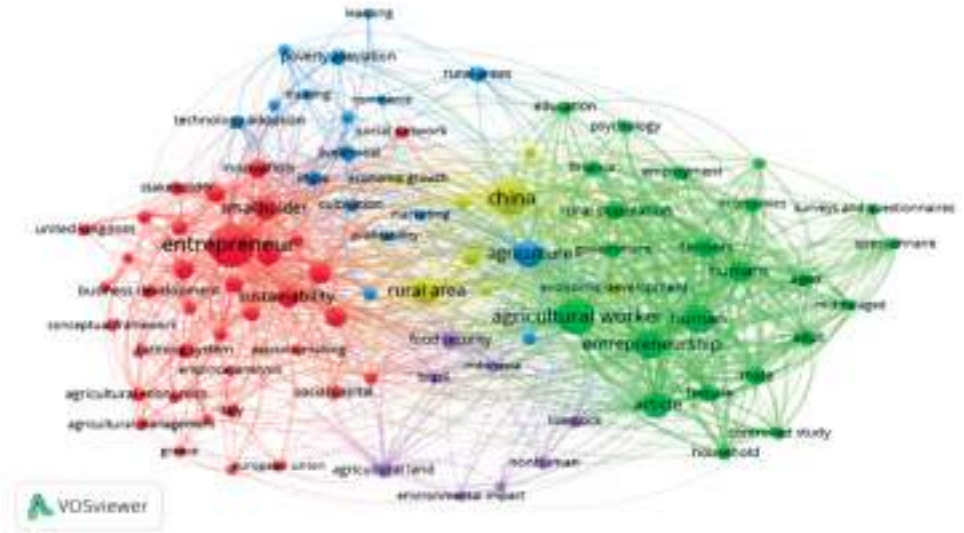


Figure 3. Network visualization of author keyword co-occurrence in agricultural entrepreneurship research

smallholder farming and rural economic growth. Among the key thematic groups, there is the focus on entrepreneurship and rural development, which is captured in the keywords: entrepreneurship, sustainability, innovation, smallholder farming, agricultural economics, and farming systems. The studies in this cluster are interested in the role of the entrepreneurial activity in enhancing the productivity of farms, the development of the rural economy, and the modernization of agriculture. The other key cluster is connected with the use of technology and livelihood development. The keywords that would be found in this group are technology adoption, training, learning, commerce and poverty alleviation. This cluster brings out the contribution of knowledge dissemination, extension services and skill development programs in improving the entrepreneurial capabilities of farmers (Hu et al., 2021). A third thematic group focuses on social and economic aspects of agriculture, and keywords are rural areas, social networks, economic growth, marketing, profitability and livelihood. These are more or less the same topics of growing interest on social capital, institutional support and market integration within the agricultural entrepreneurship research. The keywords like India, China and rural areas are also present which speaks further of the fact that a significant part of research is concentrated in developing countries in which agriculture is still a significant source of employment and income. On the whole, the co-occurrence network keyword proves that the study on agricultural entrepreneurship is tightly integrated with the topics of rural development, technological innovation, sustainability, and the livelihood of farmers.

The network index key gives a more detailed idea of thematic relationships in the literature basing on standardized keywords which are extracted as a result of database indexing systems. Index keywords also represent wider conceptual associations and research patterns as compared to author keywords.

The network visualization (Figure 4) shows some big clusters representing various aspects of the research in agricultural entrepreneurship. The former group is about entrepreneurship and rural economic development. Rural development, rural economy, farmers attitude, innovation, agro-industry and sustainability are some of the keywords that are widely used in this cluster. The words underscore the significance of entrepreneurship in improving the performance of the rural economy and encouragement of agricultural value chains. The other group of keywords is agricultural production systems and economic factors centered around the following keywords: agriculture, agricultural worker, investment, productivity, finance, and economic development. This cluster indicates the increasing significance of financial resources, institutional support, and investment of enhancing the agricultural productivity and entrepreneurship outcomes. The third cluster focuses on social and demographic specifics of rural inhabitants including such keywords as farmers, rural population, employment, household, male, female, adult, and poverty. It means that there is a high number of studies that concentrate on the socio-economic profile of farmers and what affects the entrepreneurial behavior of rural people. Anthropogenic importance of food security and sustainability in agricultural entrepreneurship research is also emphasized in the network. The keywords that may be outlined as food security, environmental impact, and agricultural land are present in the network, indicating the increase of the focus on sustainable agricultural farming practices and resource management. The strong interrelations between these clusters show that the agricultural entrepreneurship is a multidimensional notion that is shaped by the economic, social, institutional, and environmental conditions.

The collaboration network map created with the help of VOSviewer (Figure 5) displays the global network of collaborators of agricultural entrepreneurship literature. The nodes in this network will depict countries and the connections among the nodes will depict the relationship between countries in terms of collaborating research.

The United States comes out as a major center in the network of collaboration with its research being heavily collaborative with other countries including Canada, the Netherlands, China, and other European countries. This is an indication of a high research potential and global collaborative relationships that come with American universities and research centers. China also emerges as one of the

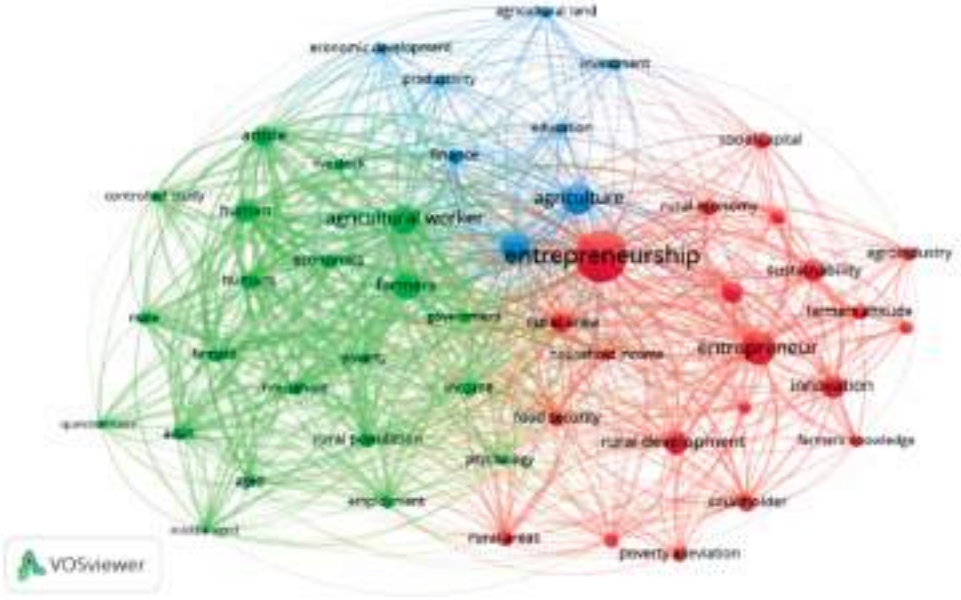


Figure 4. Network visualization of index keyword co- occurrence showing thematic clusters in agricultural entrepreneurship research

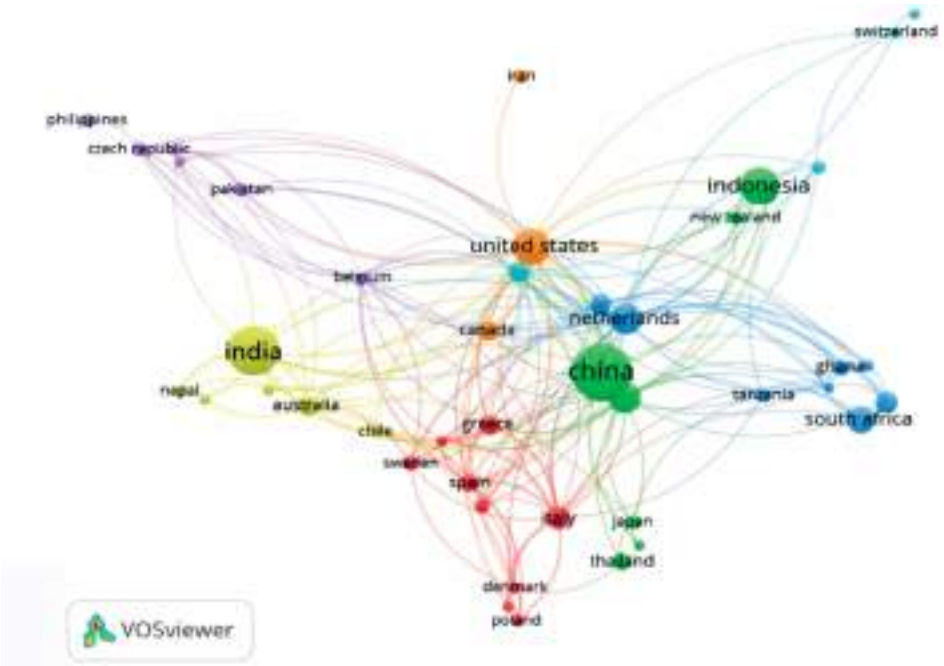


Figure 5. International country collaboration network in agricultural entrepreneurship research

key players and it makes a big cluster and is correlated to many countries like the Netherlands, Japan, Thailand and many developing countries (Dhillon, 2026). The intensive Chinese presence can be attributed to growing research expenditure by China in innovation in agriculture, rural development, and transformation of agribusiness. Another significant research cluster is India which is related to other nations, including Nepal, Australia, and Chile (Lachney et al., 2021). This group shows the increasing scholarly attention to agricultural entrepreneurship in South Asia, especially in relation to the smallholder systems of farming and rural development of livelihoods (Sarfraz et al., 2022). Another collaboration group is European countries, including Italy, Spain, Sweden, and Denmark, which employs the regional cooperation in agricultural economics and countryside development studies. Also, one can find the countries like Indonesia, South Africa, Ghana, Switzerland, and New Zealand in the network, which proves the broadening of the geographical range of the research on agricultural entrepreneurship in the various continents. The collaboration map demonstrates the rising internationalization of the research in the field of agricultural entrepreneurship and the significance of the international exchange of knowledge in addressing the most frequent issues associated with the food security, rural poverty, and sustainable agricultural development.

The collaboration of Biblioshiny and VOSviewer analysis shows that there are a number of potential directions of the research in the field of agricultural entrepreneurship. Firstly, it is the increased attention to sustainability-based entrepreneurship in which studies are concentrated on environmentally conscious cultivation methods, climate-stable agriculture, and sustainable consumption levels of resources. Second, behavioral economics and empirical research continue to study the behavior of farmers and their entrepreneurial orientation with a focus on psychological issues, knowledge, and risk-taking capacity as drivers of entrepreneurial decision-making. Third, the systems of technology adoption and innovation have become one of the areas of inquiry especially in the context of digital agriculture, precision farming, and the development of the agricultural value chain. Lastly, there is an increment in the literature on rural livelihood transformation where entrepreneurship is the main theme on how it can alleviate poverty, create employment, and diversify rural economies. These new trends prove the dynamic character of agricultural entrepreneurship studies and show the necessity in relation to modern challenges of the world of agriculture (Waltman et al., 2010).

DISCUSSION

The bibliometric analysis results demonstrate the intensive growth and the increasing scientific attention to the research of agricultural entrepreneurship in the world. The rise in publications over time through the study period shows that entrepreneurship is gradually getting accepted as a fundamental tool of enhancing agricultural productivity, rural development and food systems. The growing popularity of the studies is also the symptom of the growing significance of innovation, sustainability, and value creation in the context of contemporary agriculture. The findings also reveal that the study of agricultural entrepreneurship is very interdisciplinary as the sciences of agricultural economics, rural sociology, agribusiness management, and innovation studies are all intertwined in it (Kurtaj et al., 2024; Mansingh et al., 2025).

The variety of themes of research that include sustainability, rural development, technological innovation, and farmer livelihoods points to the fact that entrepreneurship in agriculture is not exclusive to the context of business practices but also closely related to the wider social-economic transformation within the rural context (Sirine et al., 2020; Xie et al., 2021). These findings underline the changing role of the entrepreneurial practices in dealing with the complex agriculture challenges. The collaboration network analysis shows that there are good international research collaborations between the countries. The countries, like the United States, China or India, are the key participants in the formation of trends in research in the world, and they make a great contribution to the

development of knowledge in this direction. This international cooperation is critical towards combating the global issues of concern like climate change, food security and poverty in rural areas. The collaboration networks also suggest the growing knowledge exchange both between institutions and across continents. In addition, both the keyword and index key words demonstrate the strong presence of the themes of entrepreneurship, sustainability, innovation, and rural livelihoods.

Such results imply that the research is no longer centered on the conventional agricultural production but a more holistic approach that focuses more on the entrepreneurial behavior and technological adoption and sustainable management of resources. On the whole, the findings show that the research in agricultural entrepreneurship is becoming more dynamic, multidisciplinary, and internationally connected, which is the consequence of the growing importance of sustainable agricultural development and economic growth in the rural areas.

CONCLUSION

This bibliometric study highlights the rapid evolution of research on agricultural entrepreneurship and entrepreneurial behaviour between 2016 and 2025. The findings indicate a clear shift from fragmented studies toward a more integrated and interdisciplinary research domain, driven by increasing global emphasis on sustainability, innovation, and rural development. The prominence of themes such as technological adoption, value chain development, and farmer livelihoods reflects the expanding scope of agricultural entrepreneurship beyond traditional production systems. Collaboration patterns reveal the leading role of countries such as the United States, China, and India, while also indicating growing international research linkages. The study further underscores the influence of global challenges, including climate change and food security, in shaping research priorities. Future research should focus on empirical and impact- oriented approaches to better understand entrepreneurial outcomes in agriculture. Policymakers should promote innovation ecosystems, capacity building, and institutional support to strengthen agricultural entrepreneurship and ensure sustainable rural transformation.

DECLARATIONS

Ethics approval and informed consent: As the research was carried out with bibliometric analysis, the Scopus database was used for the study, with inclusion and exclusion criteria.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The author declares that they have thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Article

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Identification and Documentation of Agricultural Indigenous Technical Knowledge among Yimkhiung Tribe, Nagaland, India

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HIGHLIGHTS

- Thirty-five indigenous technical knowledge practices were documented, with maximum practices in harvesting and post-harvest management.
- A total of 18 ITKs perceived effectiveness was measured, 17 were highly effective and one was rated effective.
- Traditional knowledge and craftsmanship are declining, highlighting the urgent need for documentation and youth involvement.

ARTICLE INFO

Keywords: ITK, Yimkhiung, Agriculture, Nagaland, Identification, Documentation.

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ABSTRACT

Nagaland, inhabited by 17 major tribes, possesses rich agricultural knowledge, with each tribe maintaining distinct customs while sharing a deep connection to nature and biodiversity. All the tribes have been practicing traditional methods of agriculture. Thus, the study was conducted out in the year 2025 with the objective to identify and document the agricultural Indigenous Technical Knowledge (ITK) among the Yimkhiung tribe of Nagaland, India. The research was carried out in the Kiphire district covering Pungro and Khongsa blocks selected purposively, and three villages from each block were chosen randomly, namely Pungro, Old Vongti, Luthur, Longkhimvong, Khong, and Mimi, with a sample size of 120. Multistage random sampling method and descriptive research design were adopted. A total of 35 agricultural ITKs were identified and documented. Assessment of Effectiveness of 18 ITKs were also measured using PEI (Perceived Effectiveness Index). However, the preservation of ITK faces obstacles, including language barriers, ethical considerations, and resource limitations. Despite these challenges, documenting ITK is essential to safeguard this invaluable knowledge and facilitate its integration into contemporary practices. Through respectful collaboration, ITK can contribute to a more resilient, culturally rich, and sustainable future for Northeast India and beyond.

INTRODUCTION

Indigenous Technical Knowledge (ITK) are time tested knowledge and experiences of the people in dealing with situations and problems in varying aspects of life, and such knowledge and practices are special to a particular culture (Rai et al., 2019). ITK is a distinctive form of traditional, localized knowledge shaped by the specific circumstances of men and women indigenous to a given geographical area (Grenier, 1998). Measures such as documentation, registration, innovation patent systems, and the creation of a sui generis framework are necessary to safeguard ITK (Rao, 2006).

Effective communication is essential for preserving, enhancing, and transmitting this wisdom. Over thousands of years, farmers have developed cost-effective methods that support national economic growth and sustainable agricultural development (Lenka & Satpathy, 2020). Over time, ethnic groups have created indigenous knowledge based on necessity, experimentation, curiosity,

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and observation in order to lessen the immediate situational issues (Talukdar et al., 2012). These eco-friendly and time-tested practices, passed down through generations, reflect deep respect for nature. Preserving them through awareness and documentation is vital before they are lost. Additionally, there are insufficient connections between indigenous knowledge and practices and contemporary technologies. ITKs contribute to agricultural goods free of pesticidal residues because they are environmentally friendly and even compatible with other management techniques (Boruah et al., 2020). By building a bridge between modern and traditional knowledge, better agriculture can be performed along with a clean, green and safe environment to live in and flourish in (Sindhu & Malik, 2020), similarly economic effect of the farmers' innovations in terms of changes in income, change in savings of stakeholders, change in capital owned and change in credit availability were observed (Nain et al., 2024).

In Nagaland main occupation is agriculture, and rice is the staple food. The Naga tribes possess a spectacular wealth of indigenous knowledge. Since time immemorial, farmers have been practicing traditional methods of agriculture (Nagi et al., 2023a). The locations of these different sites force the farmers to develop and adapt practices that suit the site's requirements. More than 73% of the state's total arable land is used for jhum farming (Vision, 2025) and has been blended into the tradition of hill's tribes (Priyadarshni et al., 2021). Development initiatives in the state should build on the traditional practices, many of which are celebrated through stories, songs, and harvest festivals. Preserving Nagaland's ITK requires systematic documentation from villages across the state. Indigenous farming methods, passed down orally and through practice, remain vital for sustaining the community (Roy et al., 2020). For decades Yimkhiung tribe in Kiphire district has been practicing ITK in their farming and which has sustained them through generations, but these methods are still largely undocumented and are often confined to the older generation. Thus, ITK is being gradually eroded and forgotten which poses a great loss to future generations. To address the lacunae, this study is undertaken to document the significance of indigenous knowledge for sustainable agriculture and its long-term practices.

METHODOLOGY

The study was conducted in the state of Nagaland, having 16 districts, of which Kiphire district was selected for the study because the main occupation in agriculture is 70 per cent (2011 census). The traditional practices of the local, Yimchungrü/ Yimkhiung tribes are closely linked to sustainable forest management, traditional agriculture, and biodiversity conservation. The district, being relatively remote and less influenced by modernization, retains a higher degree of traditional practices, making it a suitable site for documenting authentic ITKs (Kiphire District Administration, 2025). There are 5 administrative blocks in Kiphire district**.** Out of these blocks, Pungro and Khongsa blocks were purposively selected for the present study, because majority of the Yimkhiung tribes reside in these two blocks, where they still practice traditional ways of cultivation. In this study a total of 120 farmers were randomly selected for the present study. To identify and document the ITKs practices. Traditional knowledge-associated information was collected from the older generation with Prior Informed Consent (PIC) applying participatory tools such as focus group discussion, semi-structured interview method, observation and key informants' interviews.

Effectiveness or efficiency can be defined by the degree of relative usefulness of the ITKs as perceived by the farmers and measured by using the perceived effectiveness (PEI) methodology (Sundaramari, 2001) with slight modification. The index consisted of four attributes *viz*., cost effective, easy availability/accessibility, observability and sustainability, which their relevancy weightage was calculated by using the formula given below:

$$R = \frac{\Sigma riwi}{w\Sigma ni}$$

Where, R is the relevancy weightage of selected ITK, w is maximum of point continuum, n is number of respondents, r is four attributes

The respondents were asked to rate each identified ITK practice based on the four attributes on a three-point continuum: "Agree", "Undecided' and "Disagree", which were assigned the scores "3", "2" and "1" respectively. It was unrealistic to assume that every respondent would have embraced every ITK listed in this study. However, even if the respondents thought it was effective, the least popular approach could not be considered effective. As a result, only selected 18 ITKs was assessed to measure their perceived effectiveness index (PEI). The Perceived Effectiveness Index (PEI) score of a particular ITK practice was calculated using the formula.

$$PEI = \frac{W1R1 + W2R2 + W3R3 + W4R4}{R1 + R2 + R3 + R4}$$

Where, R1, R2, R3 and R4 were relevancy weights of the four attributes and W1, W2, W3 and W4 were scores obtained for the attributes of ITK practice from each respondent.

The perception of the farmers who adopted the ITKs was expressed as mean perceived effectiveness index (MPEI). To obtain the Mean Perceived Effectiveness Index (MPEI) for a particular ITK, the mean score of PEIs obtained from all the respondents for a particular ITK was calculated. Based on the MPEI score, all the ITK practices were categorized into three categories and considering their individual total scores, the respondents were then categorized on the basis of mean (μ) and standard deviation (σ)

$$\text{MPEI Score} = \frac{\text{MPEI score of Individual farmer for each ITK}}{\text{Total sample size}}$$

MPEI of 3 was regarded as the most effective while MPEI of 1 was regarded as ineffective. ITK with MPEI less than 2.0 were considered less effective. ITK with MPEI between 2-2.5 were considered as effective whereas MPEI of greater than were regarded as highly effective (Table 2). Highly effective ITKs are scientifically valid, strongly adopted and practiced and hence can be propagated without any doubt.

Table 1. Weightage scores of various attributes of ITK practice

Attributes	Relevancy weight
Cost effective	0.86
Easy availability/accessibility	0.90
Observability	0.93
Sustainability	0.96

Table 2. Distribution of selected ITK practices based on their perceived effectiveness

Category	Frequency	Percentage
Ineffective (1)	0	0
Less effective (<2)	0	0
Effective (2-2.5)	1	5.56
Highly effective (>2.5)	17	94.44
Most effective (3)	0	0
Total	18	100.00

RESULTS

Description of the documented ITKs

A total of 35 ITKS were identified and documented. The ITKs were documented and categorized under nine major agricultural practices, namely field preparation; seed selection; sowing operations; cropping pattern; plant protection; intercultural practices; harvesting and post-harvest management; weather forecasting; and livestock management.

Field preparation

A total of four ITKs were identified under field preparation, reflecting farmers' adaptation to local environmental conditions. In shaded areas (*Müzüng*), slashing is carried out during November and burning in February to allow sufficient drying of biomass, whereas in sunlit areas (*Kelim*), these operations are delayed to ensure effective burning. Traditional tools such as *Thuh* (hoe) and *Nuk* (machete) are widely used for land preparation. Additionally, terracing is practiced in jhum fields using logs and stones along slopes to prevent soil erosion and conserve moisture. Collection of debris and stubble using *Woyak* further facilitates land levelling and nutrient recycling.

Seed selection and storage

Five ITKs were documented under seed selection and storage. Farmers carefully select healthy and robust planting materials, particularly in paddy, which are sun-dried and stored in bamboo structures (*Tram*). Seeds of vegetable crops such as chilli, pumpkin, and cucumber are extracted, dried, and stored in bamboo or bottle gourd containers (*Keluh*) placed above fireplaces to prevent moisture and pest damage. Tubers such as yam are sorted based on size, with larger ones stored near fireplaces and smaller ones kept in bamboo baskets (*Mülok*) and storage houses (*Jakam*). In some cases, maize cobs are stored in earthen pots or hung near fireplaces to enhance shelf-life and prevent fungal infestation.

Sowing operations

Five ITKs related to sowing operations were identified, highlighting crop-specific and time-bound practices. Soybean is cultivated during May–June to ensure better pod formation, while kholar (kidney beans) is grown twice a year for both consumption and commercial purposes. Crop-specific planting techniques, such as slanted planting of tapioca and vertical or whole planting of taro tubers depending on size, are followed to enhance growth and yield. Sowing is generally carried out using a traditional implement known as *Kejinglim Thuh*, which is simple and efficient.

Cropping pattern

Three ITKs were documented under cropping pattern, emphasizing both ecological indicators and mixed cropping systems. Farmers rely on natural indicators such as the budding of plants like *Thüvepün* (*Bauhinia variegata*) and *Yapmapün*, as well as the call of the hawk cuckoo (*Hierococcyx sparverioides*), to determine the appropriate time for sowing. Mixed cropping is widely practiced, with rice, maize, and yam grown together in jhum fields. Creepers such as cucumber and pumpkin are planted along field boundaries, while chilli and king chilli are grown within bunds. This spatial arrangement ensures efficient utilization of space, nutrients, and moisture, while minimizing competition among crops.

Plant protection

Four ITKs were identified under plant protection, primarily based on traditional and eco-friendly approaches. Scarecrows made from bamboo and cloth are used to deter birds, while a bamboo device (*Ke Kak Kak*) produces sound to repel animals and rodents. Manual handpicking of visible pests and disposing of them in water is also practiced to reduce infestation. Additionally, ash is applied in fields as a natural pesticide, reducing reliance on chemical inputs.

Intercultural practices

Only one ITK was documented under intercultural practices, which involves timely weeding operations. The first weeding is carried out in May using the traditional tool *Thuh*, while subsequent weeding is done manually or with the same tool as needed. This practice helps in reducing competition for nutrients and supports healthy crop growth.

Harvesting and post-harvest management

A total of ten ITKs were identified under harvesting and post-harvest management, making it the most prominent category. Harvesting is often done manually, such as pinching in millets to select healthy seeds, or using tools like *Woyi* (sickle) for paddy. Crops like soybean and kholar are processed through traditional threshing and winnowing using bamboo mats (*Phiak*) and winnowers (*Phürü*).

Post-harvest practices include sun drying and storage in bamboo structures (*Tram*) to reduce moisture and enhance shelf-life. Tubers are stored in traditional storage houses (*Jakam*) that allow proper aeration. Maize is initially stored in temporary field structures (*Manji Yam*) to ensure adequate drying before being transferred to permanent storage, thereby preventing spoilage. In some villages, crops are also stored in earthen pots for long-term preservation. Cultural festivals such as *Tsak ra nean* and *Tsüngkamneo* are associated with harvesting and reflect the socio-cultural significance of these practices.

Weather forecasting

One ITK related to weather forecasting was documented. Farmers predict weather conditions based on observation of the night sky; clear skies with visible stars indicate fair weather, while cloudy skies without stars suggest the likelihood of rainfall. This reflects traditional ecological knowledge developed over generations.

Livestock management

Two ITKs were identified under livestock management. Farmers feed pigs with a mixture of maize and pumpkin to promote growth and weight gain and also provide local herbs such as Tulsi or mint to treat illness. In poultry management, hanging empty bee nests inside chicken coops is believed to enhance population and egg production. These practices reflect locally adapted and culturally rooted livestock management systems.

Perceived effectiveness of the eighteen selected ITK practices with their MPEI scores

Out of the documented 35 ITKs, a total of 18 selected ITKs perceived effectiveness were measured. Based on the perception of the respondents, 17 practices were perceived as highly effective and 1 was perceived as effective (Table 3).

DISCUSSION

Indigenous Technical Knowledge (ITK) continues to play a significant role in agricultural production and natural resource management. It reflects farmers' long-standing interaction with their local environment and contributes to sustainable farming systems. The present findings indicate that ITKs are widely practiced in the study area, supporting earlier observations that indigenous knowledge enhances both agricultural productivity and environmental conservation (Adedipe et al., 2004; Muthee et al., 2019). The reliance

Table 3. Perceived effectiveness of the eighteen selected ITK with their MPEI scores

Description of ITK identified	MPEI Score	Remarks	Farmer's rationale behind the use of the ITK
Land preparation using the local tool *Thuh*.	2.76	Highly effective	Helps in cutting, turning soil, uprooting weeds, and preparing seedbed.
Traditional terracing using logs and stones after burning.	2.88	Highly effective	Prevents soil erosion and retains nutrients.
Debris and stubbles are further cut using traditional daos/machetes called *Nuk* and collected using a traditional rake called *Woyak* and burned.	2.84	Highly effective	Facilitates leveling, controls pests and weeds, and adds nutrients.
Healthy and robust looking paddy plants are selected, dried and stored separately in bamboo storage structure *Tram* for the next cropping season.	2.63	Highly effective	Ensures better yield, drying prevents pests and mold.
Healthy vegetable seeds are extracted, dried, and stored in bamboo/ gourd containers above the fireplace for the next cropping season.	2.70	Highly effective	Ensures good yield and prevents spoilage.
Healthy yam tubers stored near fireplace and smaller ones are kept in bamboo basket *Mülok* and store in storage house *Jakam*.	2.80	Highly effective	Improves shelf-life.
Maize cobs, garlic, millets etc are tied together and hung near the fireplace.	2.83	Highly effective	Heat prevents mold damage.
Seeds and tubers/rhizomes are sown using a small local implement *Kejinglum Thuh*.	2.89	Highly effective	Easier and efficient sowing.
Taro (Colocasia esculenta) tubers are cut and planted vertically.	2.78	Highly effective	Enhances germination.
Mixed cropping: Rice, yam, maize planted on bunds. Creepers on sides and chilli in between the bund structure.	2.90	Highly effective	Reduces crop failure risk, ensures efficient space and nutrient use.
Weeding is done using a local tool called *Thuh*.	2.88	Highly effective	Removes regrowth and prevents competition.
Millets are harvested manually and kept in harvesting basket *khishang* or *khituh*.	2.80	Highly effective	Helps select best seeds.
Yam, ginger etc., are harvested using *Kejinglim Thuh* and put in the harvesting basket *Jimtsah hah*.	2.66	Highly effective	Prevents sprouting and quality loss.
Soyabean and kholar are harvested and collected in bamboo mat *Phiak* which is beaten to collect the seeds. The seeds are collected and winnowed using *Phürü*	2.84	Highly effective	Separates grains and cleans produce.
Paddy is harvested with local sickle *Woyi*.	2.78	Highly effective	Saves time and effort.
The harvested paddy is collected and beaten with a stick. The beaten seeds are collected and winnowed using *Phürü*	2.89	Highly effective	Separates grains and cleans produce.
Harvested crops are sundried and stored in a bamboo basket *Tram*.	2.93	Highly effective	Reduces moisture and increases shelf-life.
Clear sky with stars indicates good weather	2.49	Effective	Traditional weather prediction method.

on ITKs despite the availability of agrochemicals suggests that these practices remain relevant due to their cost-effectiveness, ecological compatibility, and adaptability to local conditions

The study documents a total of 35 ITKs across different agricultural operations, with the highest concentration observed in harvesting and post-harvest management (10), followed by sowing operations (5) and seed selection (5). This trend indicates that farmers place greater emphasis on minimizing post-harvest losses and ensuring food security, which aligns with findings of Sarkar et al. (2022), who report the extensive use of ITKs in post-harvest handling and storage in the Northeastern Hill Region (NEHR). The relatively fewer ITKs identified in weather forecasting suggest either a gradual decline in traditional predictive practices or a shift towards more observable and immediate indicators, although such practices still reflect deep ecological knowledge.

The widespread use of practices such as logwood lining across slopes to prevent soil erosion demonstrates a strong alignment with sustainable land management principles. This finding corroborates earlier reports by Das et al. (2025), emphasizing the importance of such techniques in jhum agroecosystems of hilly regions. Traditional slope management practices effectively reduce soil erosion and enhance nutrient retention in shifting cultivation systems (Vliet et al., 2012). This indicates that ITKs are not merely traditional but are grounded in sound ecological principles. Similarly, the use of ash as a natural pesticide confirms the observations of Hakbiji (2002), indicating that farmers continue to adopt low-cost and environmentally safe pest management strategies. Livestock-related practices, such as feeding pigs with a mixture of maize and pumpkin for weight gain and the use of tulsi (*Azadirachta indica*) for medicinal purposes, also show consistency with previous findings (Singh et al., 2019; Vásquez et al., 2025). Indigenous pest management practices are recognized for reducing chemical dependency and preserving biodiversity (Isman, 2006). Another important observation is the reliance on ecological indicators such as plant phenology and bird behavior for decision-making in cropping operations which shows that traditional ecological knowledge (TEK) plays a critical role in climate adaptation and seasonal forecasting (Berkes et al., 2000; Speranza et al., 2010). Such practices demonstrate farmers' deep understanding of ecosystem dynamics, which remains relevant under changing climatic conditions.

The dependence on traditional tools and implements across agricultural operations further reflects the adaptability of ITKs to the geographical constraints of Nagaland. The mountainous terrain limits the use of modern machinery, thereby reinforcing the continued use of indigenous tools. This observation supports the findings of Singh and Devi (2020), who note that traditional implements remain integral to farming in hilly regions. Moreover, these tools are designed to minimize soil disturbance, thereby contributing to sustainable land use, which is also consistent with the observations of Dutta et al. (2025). Despite their effectiveness, the study also reveals a concerning trend regarding the gradual erosion of ITKs. The knowledge and skills associated with traditional tools and practices are primarily confined to older generations, with limited transmission to younger individuals. This finding is in agreement with Benjongtoshi et al. (2023) and Nagi et al. (2023b), who highlight the risk of loss of indigenous knowledge due to generational shifts and changing socio-economic conditions. The decline in knowledge transmission may lead to the disappearance of valuable practices unless appropriate measures are taken for their documentation and preservation.

Overall, the findings demonstrate that ITKs remain highly relevant in ensuring sustainable agricultural practices, particularly in ecologically fragile regions. At the same time, the observed decline in their transmission underscores the urgent need for systematic documentation, validation, and integration of ITKs with modern scientific approaches to ensure their continued relevance and application.

CONCLUSION

The study establishes that Indigenous Technical Knowledge remains an integral component of agricultural practices among the Yimkhiung tribe, contributing significantly to sustainability, resource conservation, and livelihood security. The identification and documentation of diverse ITKs across farming operations indicate their continued relevance and adaptability to local ecological conditions. The predominance of practices in harvesting and post-harvest management highlights farmers' emphasis on minimizing losses and ensuring food security. The findings affirm that ITKs serve as effective, low-cost, and environmentally compatible alternatives that complement modern agricultural approaches. However, the gradual erosion of such knowledge due to generational gaps underscores the need for systematic documentation, validation, and dissemination. Strengthening the integration of ITKs with scientific innovations and promoting their transmission among younger generations emerges as essential for achieving resilient and sustainable agricultural systems.

DECLARATIONS

Ethics approval and informed consent: All authors concur with the submission, and informed consent was sought and received from all respondents.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The author declares that they have thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Article

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Knowledge Level of Kewda Cultivation Farmers in Southern Odisha

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HIGHLIGHTS

- Respondents exhibited significant knowledge regarding climatic requirement, soil suitability, flowering behaviour, harvesting methods and planting material.
- Significant knowledge deficiencies were observed in nutrient management, spacing, manuring practices, intercultural operations and desuckering.
- Correlation and regression analysis revealed that education, family size, occupation, information sources, and annual income significantly influenced knowledge levels of respondents.

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ABSTRACT

The study was conducted in 2024 in Ganjam district of Odisha to assess the knowledge level of farmers regarding recommended Kewda cultivation practices using an ex post facto research design. Data were collected from 83 Kewda flower growers through a structured interview schedule, employing purposive and simple random sampling techniques. The results revealed that respondents demonstrated relatively higher knowledge of ecological conditions and traditional field-based practices. The findings further indicated that farmers were actively involved in planning, decision-making and adoption of innovative cultivation practices, while facing constraints in value addition and distillation activities. Correlation and regression analysis indicated that variables such as education, innovativeness, planning ability, and decision-making capacity had a positive and significant relationship with the knowledge level of respondents. The study concludes that although Kewda cultivation provides substantial livelihood opportunities in coastal Odisha, there is a need for targeted extension interventions, capacity-building programmes, and skill-oriented training, particularly in post-harvest and value addition practices, to enhance farmers' knowledge and adoption of improved technologies.

INTRODUCTION

Kewda (*Pandanus odorifer*), or kia locally, is a globally significant fragrant plant that is used in the production of perfume, traditional medicine, and religious rituals due to its fragrant flowers and leaves (Singh and Parle, 2016). In India, the cultivation of kewda has significant economic and cultural significance, particularly in

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the Odisha state. Ganjam district alone produces 85-90 percent of the total production of kewda flowers in the country (Senapati, 2023). Pandanus odorifer is a small, gregarious, perennial evergreen with a flexible trunk, and with the help of brace roots, it grows in the form of a dense grove in damp areas, regardless of the amount of flooding (Solomon et al., 2020). The cultivation of Kewda is primarily associated with small farming and local knowledge regimes. In some villages, including Kirtipur of Ganjam district, most of the households rely on kewda flowers as a leading source of income (Gaonconnection.com, 2022). Small and marginal farmers are dependent on the crop, as it is a source of regular income, and women are essential in gathering male flowers in harsh conditions (Acharya, 2025).

The cultivation of Kewda helps to empower rural livelihoods as it offers the small and marginal farmers income. Plants become mature in 4-5 years and live up to 40-45 years, blooming every month in the first flowering stage with four flowers (Padhy et al., 2016). Kewda plants begin flowering 5–7 years after planting, with male plants blooming three times a year and peak flowering during July–September (Panda et al., 2012). Despite its production potential, the kewda industry in Ganjam district is declining due to reduced profitability and policy constraints, leading to fewer collectors and about 50 distillation units (Panigrahi, 2019). Women play a crucial role in agricultural livelihoods, and their participation in farm-based enterprises reflects growing entrepreneurial potential driven by knowledge, innovation, and planning ability (Kumari et al., 2025). A more market- and business-oriented strategy is gradually replacing subsistence-based methods in the agriculture sector. Recognising the importance of fostering agripreneurship, various organisations are actively promoting entrepreneurial development among farmers through capacity-building initiatives and institutional support (Kademani et al., 2024). Intercropping *Pandanus* with arecanut has been reported to improve soil microbial diversity and maintain ecological balance in tropical plantation systems (Zhong et al., 2022). Pandanus leaves are typically harvested twice a year, during April–May and December–January, using sickles or long-handled tools to cut leaves from taller plants (Naseer, 2015). Non-governmental organisations (NGOs) should collaborate with Krishi Vigyan Kendras, agricultural colleges, and research institutions to strengthen scientific capacity-building initiatives for farmers (Padhy et al., 2026).

Although kewda cultivation is recognized for its livelihood potential, there is limited empirical evidence on farmers' knowledge of recommended practices. This gap restricts targeted extension and capacity-building efforts. Assessing farmers' knowledge is essential to identify gaps between existing practices and scientific recommendations, helping design interventions to enhance productivity, income, and sustainability. The present study aims to analyse the knowledge level of farmers regarding Kewda cultivation practices.

METHODOLOGY

The study was conducted in 2024 in Ganjam district of Odisha. The district was purposively selected as it is the major Kewda-growing region of the state, contributing nearly 85–90 per cent of the country's production (Senapati, 2023). It also has a high concentration of farmers engaged in kewda cultivation and flower collection, making it suitable for assessing farmers' knowledge of cultivation practices. Two blocks, namely Chatrapur and Rangeilunda, were selected randomly from the district. From each block, four Gram Panchayats were selected through simple random sampling. A comprehensive list of kewda growers in the selected Gram Panchayats was obtained from the District Horticulture Department, Ganjam and around 15% respondents were selected from each Gram Panchayat. Based on this list, a total of 83 respondents were selected. The respondents comprised active kewda growers in the study area. Regarding the sample size (n = 83), it is justified as it ensured proportional representation of kewda growers across selected Gram Panchayats and was adequate for conducting meaningful statistical analysis within the constraints of time and field accessibility.

The term knowledge level in the current study is used to refer to the range and depth of knowledge that the farmers possess concerning the suggested practices of the Kewda cultivation and this includes aspects such as, how to plant the plants, how to manage the nutrients, intercultural operations, flowering, and harvesting practices. The present study employed a structured interview schedule that was elaborated based on a literature review and the consultation of the experts in the subject matter in analyzing the level of knowledge of respondents concerning the recommended practices in cultivating Kewda. The answers were taken on a three-point basis (strongly agree, agree and disagree) giving 3, 2 and 1, respectively. Even though the three-point scale (strongly agree, agree and disagree) is a simplified measure of knowledge, it was adopted so that it would be easy to comprehend by respondents of different educational backgrounds, as well as to get the respondents to respond accurately during personal interviews. The knowledge gap was assessed by comparing the maximum obtainable score with the mean score obtained for each practice and expressing the difference as a percentage. The collected data were analysed using descriptive statistics such as frequency, percentage, mean and standard deviation, while correlation and multiple regression analysis were used to examine the relationship between selected socio-economic variables and the knowledge level of respondents.

RESULTS

Table 1 indicates that the respondents are categorised as poor/ high based on the mean score. The findings reveal a clear dichotomy between farmer's operational knowledge of ecological and operational practices and their limited understanding of cultural practices.

Table 1 presents the mean knowledge scores of respondents regarding recommended Kewda cultivation practices. The results reveal considerable variation in the knowledge level of farmers across different practices. Knowledge was measured using a three-point scale (Fully known = 3, Partially known = 2, Not known = 1). Based on the scoring procedure, knowledge levels were categorized as low (mean score < 2.00), and high (mean score ≥ 2.00). The findings indicate a clear variation in farmers' knowledge across different components of kewda cultivation.

Practices related to nutrient management and certain cultural operations recorded relatively low mean scores. These included

Table 1. Knowledge of Recommended Kewda Cultivation Practices

Practices	Mean Score	Low/ High
Nitrogen application of 12 kg/acre	1.181	Low
Manure of 1-2 basket per plant applied before planting	1.217	Low
Phosphorus application of 6 kg/acre	1.277	Low
Applying 60 g N, 30 g P & 30 g K per plant	1.446	Low
Seed also used as planting material	1.530	Low
Legumes grown initially as intercrop	1.578	Low
Main season of flowering in July – August	2.976	High
Flower collected in early morning	2.964	High
Comparatively high rainfall	2.940	High
Well drained sandy soil	2.928	High
Cuttings to be scattered in ground for 2-3 days	2.855	High
Selling collected flowers same day to distillers/ traders	2.831	High
Providing water during summer to sustain vegetative growth	2.771	High
Fertilizer to be applied in June	2.747	High
Low night temperature not desirable	2.651	High
Weeding not required due to salinity	2.518	High
Spacing at 8-10 meters distance	2.361	High
Desuckering after 3 years of planting	2.024	High

recommended nitrogen application (Mean = 1.181), application of manure before planting (Mean = 1.217), phosphorus application (Mean = 1.277), recommended fertilizer dose per plant (Mean = 1.446), use of seed as planting material (Mean = 1.530) and growing legumes as intercrop (Mean = 1.578). Since these mean values were less than the midpoint of the scale (2.0), they indicate a relatively low level of knowledge among farmers regarding these scientific cultivation practices.

In contrast, respondents demonstrated relatively higher knowledge of ecological conditions and traditional field based practices. The highest mean score was observed for knowledge about the main flowering season (Mean = 2.976), followed by collection of flowers in early morning hours (Mean = 2.964), requirement of comparatively high rainfall (Mean = 2.940), and suitability of well-drained sandy soil (Mean = 2.928). Similarly, practices such as post-harvest handling of cuttings, same-day marketing of flowers, providing irrigation during summer, and timely fertilizer application also recorded higher knowledge levels.

The findings indicate that farmers have stronger experiential knowledge of climatic conditions, harvesting, and marketing practices, while their knowledge of nutrient management and improved agronomic practices is comparatively low.

The mean score of each variable was computed to compare the different domains of knowledge related to Kewda cultivation practices. The results are presented in Table 2.

Table 2 presents the knowledge gap in recommended Kewda cultivation practices among the respondents. The knowledge gap was determined by comparing the maximum obtainable score with the mean score obtained for each practice, indicating the extent of deviation from the recommended level of knowledge.

The analysis revealed that relatively higher knowledge gaps were observed in practices related to nutrient management and

Table 2. Comparative Analysis of Knowledge Gap (n=83)

Knowledge	Average Mean Score	Gap (%)
Soil suitability	2.71	9.66
Favourable climate	2.78	7.33
Planting material use	2.43	19.00
Planting	2.70	10.00
Nutrient management	2.00	33.33
Cultural management	2.27	24.33
Flowering	2.91	3.00
Harvesting	2.90	3.33

intercultural operations, indicating limited awareness of recommended scientific practices. In contrast, lower knowledge gaps were observed for ecological conditions, flowering behaviour, harvesting and marketing practices, which farmers commonly experience in their day-to-day cultivation activities.

This pattern suggested that while farmers have good practical knowledge derived from experience, there remains a considerable gap in scientific crop management practices, particularly nutrient application and improved cultural operations. Therefore, extension interventions, farmer training programmes and demonstrations should focus on these areas to improve the adoption of recommended Kewda cultivation practices.

The results obtained from the co efficient of co relation analysis of the collected data have been indicated in Table 3.

Table 3. Association between Socio-economic Attributes and Knowledge Level (Correlation) (n=83)

Attribute	'r' value	't' value
Age	-0.191	-1.75
Caste	-0.121	-1.097
Education	0.372**	3.607
Farm holding size	-0.007	-0.0630
Family type	-0.059	-0.532
Family size	0.487**	5.020
House type	-0.077	-0.695
Occupation	-0.285*	-2.677
Extension contact	-0.089	-0.804
Information sources use	-0.355**	-3.417
Cosmopolite behaviour	0.133	1.207
Social aptitude	0.135	1.227
Economic aptitude	0.422**	4.192
Annual Income	-0.351**	-3.375

****** Significant at the 0.01 level; * Significant at the 0.05 level

The correlation analysis revealed that the attributes economic aptitude, family size and education had a positive and significant impact in enhancing the knowledge level of the respondents.

Education (r = 0.372**) showed a positive and highly significant relationship with the knowledge level indicating that farmers with higher educational attainment tended to possess better knowledge regarding recommended kewda cultivation practices. Education appeared to enhance farmers' ability to understand technical information and adopt improved agricultural practices. Family size (r = 0.487**) also exhibited a positive and significant relationship with knowledge level. This may be attributed to the fact that larger families often have more members involved in

agricultural activities, there by facilitating exchange of information and shared learning related to cultivation practices.

Economic aptitude (r = 0.422**) had a positive and significant association with knowledge level. Farmers with higher economic orientation are generally more motivated to seek information, adopt improved practices and manage their farming activities in a more efficient manner.

Occupation (r = –0.285*) showed a negative but significant relationship with knowledge level suggesting that respondents engaged in non-farm occupations or multiple livelihood activities had less time and involvement in kewda cultivation, resulting in comparatively lower knowledge regarding recommended practices.

Information sources use (r = –0.355**) also showed a negative significant relationship indicating that the respondents relied more on traditional or informal knowledge sources rather than formal extension channels. Limited access to reliable information sources may have influenced their knowledge level regarding scientific cultivation practices.

Annual income (r = –0.351**) showed a negative significant relationship with knowledge level. This may be because some farmers with higher income derived their earnings from non-agricultural sources and were less dependent on kewda cultivation, leading to relatively lower attention to technical knowledge of the crop.

To assess the influence of selected socio-economic attributes on the knowledge level of Kewda growers, a multiple regression analysis was carried out. The results are presented in Table 4.

A multiple regression analysis was carried out to determine the influence of selected socio-economic attributes on the knowledge level of kewda growers. The results are presented in Table 4. The coefficient of determination (R^2 = 0.651) indicated that 65.1 per cent of the variation in the knowledge level of respondents was explained by the selected socio-economic variables included in the model. The adjusted R^2 value (0.580) suggests that the model explains a substantial proportion of variation in the dependent variable, indicating a reasonably good fit of the regression model. Education showed a positive and significant influence on knowledge level (β = 3.812, $p < 0.01$), indicating that respondents with higher education possessed better knowledge regarding recommended kewda cultivation practices, as education enhanced their ability to access and understand technical agricultural information. Family size also had a positive and highly significant effect on knowledge level (β = 6.232, $p < 0.01$). Larger family size facilitated sharing of agricultural information and collective involvement in farming activities, thereby improving knowledge acquisition.

There was a statistically significant negative effect on family type (0.05 = -10.824, $p < 0.05$). This shows that the respondents in some types of families were more likely to be less knowledgeable in terms of recommended practices of Kewda cultivation, perhaps because of variations in decision-making processes and participation in farming activities. Occupation was a significant (negatively) and highly significant (= -7.248, $p < 0.01$) factor that indicated that a respondent who had non-farm or multiple occupations that involve livelihood was more likely to possess lower knowledge perhaps because of the reduced time and attention that would be paid to Kewda cultivation. The use of information sources also indicated negative significance (2 = -2.661, p = 0.01) indicating that informal or traditional sources of information were a greater source of information in comparison with formal extension channels.

The economic aptitude had a negative and statistically significant regression coefficient (2 = -2.134, p = 0.00) which meant that economic aptitude was negatively related to the level of knowledge of respondents on the recommended practices of Kewda cultivation. This was an implication that farmers possessing greater economic potential were more likely to have a comparatively low-level of knowledge in the current study. The results implied that economically inclined farmers may have diversified their livelihoods activities and given relatively lesser concerns to the acquisition of technical knowledge specific to the Kewda production. Annual income also showed a negative and significant influence (β = –6.186,

Table 4. Contribution of Socio-economic Attributes to Knowledge Level (Regression) (n=83)

Attribute	Coefficients				
	Unstandardized Coefficients		Standardized Coefficients	't' value	Probability
	Beta	Std. Error	Beta		
(Constant)	158.785	13.133		12.091	.000
Age	-3.410	2.058	-.183	-1.657	.102
Caste	-.452	2.084	-.026	-.217	.829
Education	3.812	1.135	.095	3.358	.003**
Farm holding size	-.901	1.636	-.095	-.551	.584
Family type	-10.824	4.259	-.518	-2.541	.013
Family size	6.232	2.005	.638	3.108	.003**
House type	-.314	1.789	-.022	-.176	.861
Occupation	-7.248	1.879	-.081	-3.857	.000**
Extension contact	-.798	.846	-.133	-.943	.349
Information sources	-2.661	.603	-.161	-3.749	0.000**
Cosmopolite behaviour	.997	.812	.182	1.227	.224
Social aptitude	.543	.591	.114	.919	.361
Economic aptitude	-2.134	.443	-.044	-4.817	.000**
Annual Income	-6.186	1.986	-.017	-3.114	.004*

a. Dependent Variable: Knowledge; R^2=0.651, Adj R^2=0.580, Std. error= 6.751

$p < 0.05$). This implied that respondents with higher income levels, possibly derived from multiple sources, were less dependent on Kewda cultivation and therefore less inclined to acquire in-depth technical knowledge of the crop.

Therefore, it was suggested that extension functionaries should consider these significant socio-economic attributes while designing and implementing educational programmes, training, and extension strategies to enhance the knowledge level of farmers regarding recommended Kewda cultivation practices.

DISCUSSION

The findings revealed that farmers possessed relatively poor knowledge and adoption of practices related to nutrient management and scientific crop inputs in Kewda cultivation. This suggested limited awareness among respondents regarding recommended nutrient management practices which might be attributed to inadequate access to formal extension services and soil testing facilities. In addition, there is also a prevailing perception among farmers that Kewda can grow successfully under low-input conditions, which might have discouraged them from adopting recommended fertilizer and nutrient management practices. The observed imbalance indicated that farmers largely relied on indigenous knowledge systems rather than formal extension recommendations. Therefore, to address this knowledge gap, it was necessary to strengthen extension interventions. Priority should be given to capacity-building programmes emphasizing balanced nutrient management and scientifically-based crop-management practices. Extension approaches such as on-farm demonstrations, farmer field schools, skills-based training programmes, and advisory services were found to be effective in enhancing the knowledge level of farmers and promoting the adoption of improved cultivation practices. This finding correlates with the studies conducted in different setting revealing farmers' significantly higher adoption of improved technologies highlighting the positive impact of extension interventions on technology uptake (Nain and Bhagat, 2005; Nain and Chandel, 2013; Raina et al., 2014; Kumar et al., 2020; Kumar et al., 2022). In addition, soil health card programmes and location-specific advisory services supported farmers in understanding balanced nutrient application. The integration of indigenous knowledge with scientific recommendations through participatory and context-specific extension strategies enhanced farmers' acceptance and adoption of improved practices, which ultimately contributed to increased productivity and sustainability in Kewda cultivation.

Correlation analysis revealed a positive and significant relationship between the education level of the respondents and their knowledge level. This indicated that farmers with higher educational attainment possessed greater knowledge regarding recommended Kewda cultivation practices. Education enhanced farmers' ability to understand technical information, interpret extension messages and adopt improved agricultural practices. Additionally, family size was found to have a strong positive relationship with the level of knowledge. Large families facilitated the sharing of agricultural skills, increased the availability of labour and promoted the exchange of information among members, thereby contributing to higher knowledge levels. The regression model further provided insight that the combined effect of the selected socio-economic variables explained variations in the knowledge level of the respondents, although the strength and statistical significance of individual factors differed.

CONCLUSION

This study examined how particular socioeconomic variables affected the knowledge of the farmers concerning the Kewda cultivation practices in the Ganjam district of Odisha. The discussion of the personal activities presented that growers had a relatively higher level of knowledge of climatic appropriateness, flowering period, harvesting time, irrigation during summer, spacing among plants and post harvesting practices. These competencies are largely derived from native indigenous knowledge gained in the course of long-term farming experience. Contrary to that, women who had knowledge about science based, input intensive practices, such as nutrient management, the rates of recommended fertilizer application, manure use, intercropping with legumes, and the use of better planting material, had significantly lower scores. The socioeconomic analysis showed that the overall knowledge of farmers had a statistically significant positive impact of education level and family size. As a result, the findings indicate that extension services should be improved through capacity-building programmes, on-farm demonstrations, and geographically-designed advisory services to align the indigenous knowledge of people with scientific principles, and hence improve productivity and sustainability of Kewda cultivation.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the respondents and their organisations regarding the study during the course of the data collection.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors declare that during the preparation of this work, they thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Article

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Bibliometric Analysis of the Role of Artificial Intelligence in Enhancing Agricultural Extension Services

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HIGHLIGHT

- Research output increased rapidly after 2016, peaking in 2022 with significant global scholarly attention.
- Recent keyword trends reveal growing emphasis on IoT, deep learning, and agricultural robotics in digital extension models.
- The literature demonstrates strong global collaboration, averaging 11.5 co-authors per publication with significant international partnerships.
- International co-authorship rate of 22.85% highlights strong global collaboration in AI-driven agricultural research.

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ABSTRACT

Agricultural extension services are still crucial to rural development and global food security; traditional methods frequently have issues with scalability, cost and farmer-specific customisation. Artificial intelligence (AI) offers a new solution to overcome these issues by offering predictive, data-driven and context-specific advisory systems. 337 papers on AI in agricultural extension that were indexed in Scopus between 2010 and 2025 were examined in this study using bibliometric analysis. Biblioshiny and VOS viewer were used in the analysis to map authorship patterns, country-level contributions, publishing trends and theme clusters. It is evident that the research activity grew after 2016 and reached a peak in 2022 at an annual growth rate of 2.33%. The area is extremely collaborative and interdisciplinary, with the United States, China and India providing the most work globally, with an average of 11.5 co-authors per manuscript. Keyword and thematic analysis show that more advanced applications like machine learning, deep learning, IoT, and agricultural robotics have replaced earlier efforts on digital infrastructure. The results indicate that hybrid systems, in which AI supplements human knowledge to provide inclusive, moral, and sustainable advisory services, will be the most successful extension models in the future.

INTRODUCTION

The diffusion of innovations theory, which describes how new practices and technologies spread among communities, has historically served as the foundation for agricultural extension. The Diffusion of Innovations Theory remains relevant in the AI era, as the adoption of AI-based advisory systems continues to depend on communication channels, farmer characteristics, and institutional support. Thus, AI-driven extension represents an evolution of diffusion processes rather than a departure from them (Chen & Li, 2022). Almost half of the world's workforce is employed in agriculture, which continues to be the main source of income for billions of people and the foundation of rural economies worldwide. In addition to being essential for food security, ensuring sustainable agricultural productivity and resilience is also critical for rural development and poverty alleviation (Sahoo et al., 2025). In order

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to ensure that scientific discoveries, technological advancements and best practices actually reach the farmers who need them most, extension serves as a liaison between research institutions and farming communities. For many years, in order to fulfil their mandate, extension services relied on printed materials, farmer field schools, farm visits, demonstration plots and interpersonal communication (Bernet et al., 2001; Nain et al., 2015; Inutan et al., 2025).

Through the use of radio, television, mobile phones and eventually internet-based platforms, information and communication technologies (ICTs) have made it possible to distribute knowledge across geographic borders (Hassan & Mirza, 2020). However, AI, which has started to change the entire essence of extension services has emerged as the true disruptive force (Pavaloaia & Necula, 2023; Haleem et al., 2022). The traditional extension methods which frequently give general suggestions AI systems are able to evaluate massive datasets such as weather forecasts, soil quality, insect occurrence and market trends and provide context-specific guidance that is customised for specific farmers or communities (Jayasingh et al., 2024). Farmers' basic photos can be used by mobile applications using AI-driven image recognition to diagnosis crop problems. Chatbots can communicate with farmers in their native tongues via natural language processing technology, which breaks down literacy hurdles and provides 24/7 consulting services (Asthana & Bhujade, 2025). The digital divide is still evident since many farmers lack mobile phones with dependable internet access or the literacy to utilise AI-enabled platforms (Atapattu et al., 2024). Extension organisations may strategically deploy resources, prioritise treatments, and identify areas at high risk of crop failure with the use of predictive models (Rane et al., 2024). AI systems can discover new concerns and knowledge gaps by analysing farmer questions and behavioural patterns. These qualities are a significant departure from typical extension's reactive, one-size-fits-all approach (Meshram et al., 2025).

Ethical considerations around data security, ownership and trust are especially important when farmers are forced to reveal sensitive information. Additional reasons to be concerned include algorithmic biases, which occur when models trained on global or non-representative datasets fail to reflect local reality (Bahangulu & Owusu-Berko, 2025). The most effective hybrid systems in the future will likely be those that employ AI to complement human extension workers rather than to replace them (Huang et al., 2025; Schubert & Barrett, 2024).

METHODOLOGY

This study employed a bibliometric research approach to systematically evaluate and map the scholarly literature concerning the application of Artificial Intelligence (AI) in improving agricultural extension services. A quantitative technique called bibliometrics enables academics to assess cooperation patterns, publishing trends, citation effect and the intellectual framework of an area of study. Bibliometric analysis offers a suitable way to identify important players, emerging topics and knowledge gaps that guide future research and policy orientations. This study evaluates the application of AI in agricultural extension services from 2010 to 2025 using bibliometric analysis. The primary data source was Scopus, a well-known database of reputable scientific publications, because of its extensive indexing of peer-reviewed journal articles and conference sessions. Using the terms "Artificial Intelligence," "Extension" and "Services," a thorough search produced an initial dataset of 629 articles. Following the application of inclusion criteria, which included eliminating duplicates, keeping only English-language journal articles, conference papers and book chapters and eliminating irrelevant items, the dataset was reduced to 337 articles, which were then exported in CSV format for analysis. Bibliometric analysis was performed using the Biblioshiny package in RStudio with Vosviewer, which made it possible to evaluate publishing trends, frequently used terms and research contributions by country (Linnenluecke et al., 2020). Key researches included tree map visualisation for hierarchical keyword representation, trend analysis to see annual publication patterns and co-occurrence network analysis to find study subjects. Scopus results were used to evaluate the regional distribution of research output. Visualisations and statistical findings demonstrated the evolution and key areas of research in AI-driven sustainable agriculture. Strict parameters were adhered to ensuring the validity and reproducibility of the findings. The analysis was interpreted through the lens of the Diffusion of Innovations Theory, linking publication trends, collaboration patterns and thematic evolution with stages of innovation diffusion.

RESULTS

Table 1 shows that the bibliometric dataset on artificial intelligence in agricultural extension services, which spans the years 2010 to 2025, provides a comprehensive picture of the state of the subject. Over the course of these 15 years, 337 documents from 152 sources have been published, demonstrating a steady but low annual growth rate of 2.33%. The literature is very new and has garnered significant scholarly attention with an average document age of 6.22 years, 10.99 citations per document and a total of 3053 references cited. 3337 Keywords Plus (ID) and 3953 Author's Keywords (DE) highlight the field's broad subject scope, which ranges from technical AI techniques to agricultural and extension applications. Authorship patterns reveal a highly collaborative research culture with 2419 authors contributing to the dataset and no single-authored documents identified. The fact that each paper usually has 11.5 co-authors and that over a quarter (22.85%) of publications are the product of transnational cooperation demonstrates the global and networked nature of this field of study. While journal articles (110, 32.6%) provide more coherent contributions, conference papers (193, 57.3%) make up the bulk of document categories, demonstrating the quickly evolving nature of AI-related extension research. Smaller but noteworthy percentages that offer contextual perspectives and syntheses include book chapters (16, 4.7%) and review papers (18, 5.3%). These patterns indicate that AI in agricultural extension is still an emerging but rapidly consolidating field, where high collaboration reflects the interdisciplinary nature of the domain and the need for integrating technological, agricultural and socio-economic expertise for effective advisory systems.

Table 1. Bibliometric Data Set

Description	Results
Main information about data	
Timespan	2010:2025
Sources (Journals, Books, etc)	152
Documents	337
Annual Growth Rate %	2.33
Document Average Age	6.22
Average citations per doc	10.99
References	3053
Document contents	
Keywords Plus (ID)	3337
Author's Keywords (DE)	3953
Authors	
Authors	2419
Authors of single-authored docs	0
Authors collaboration	
Single-authored docs	0
Co-Authors per Doc	11.5
International co-authorships %	22.85
Document types	
Article	110
Book chapter	16
Conference paper	193
Review	18

Word cloud of keyword

The field's prevailing topics and intellectual framework may be seen in the keyword treemap of publications on artificial intelligence in agricultural extension services. Fundamentally "artificial intelligence" is by far the most common term, occurring 239 times (27%), highlighting its significance as the unifying idea across investigations. This is surrounded by strong theme clusters such as "decision support systems" (42; 5%), "decision making" (35; 4%) and "learning systems" (34; 4%) that emphasise the application of AI to enhance extension results and farmer-level advising procedures. The technological basis of research is highlighted by terms like "internet of things" (30; 3%), "web services" (24; 3%), "big data" (14; 2%) and "cloud computing" (12; 1%), which denote the integration of linked devices, data analytics and cloud infrastructure into AI-driven extension models. The most popular computational tools are suggested by keywords that indicate particular methodological approaches such as "machine learning" (16; 2%), "deep learning" (11; 1%) and "data mining" (9; 1%). Application-oriented terms like "agriculture" (8; 1%), "ecosystems" (9; 1%) and "virtual reality" (12; 1%) emphasise the contextual emphasis on agricultural systems, sustainability, and immersive extension platforms. Cross-domain terms such as "sales" (9; 1%), "health care" (10; 1%) and "e-learning" (10; 1%) show interdisciplinary borrowing and the application of AI concepts to agricultural settings. Even though AI itself acts as the discourse's anchor, the figure illustrates how research momentum is distributed across clusters of decision-making support, IoT integration, big data analytics and immersive technologies, indicating a shift from theoretical exploration to practical technologically enabled extension solutions. This progression reflects the diffusion of increasingly complex innovations, consistent with the Diffusion of Innovations Theory. This suggests a shift from conceptual research toward practical decision-oriented AI applications in extension systems.

Keywords analysis

The keyword trend analysis graphic clearly illustrates the evolution of artificial intelligence research emphasis in agricultural extension services between 2010 and 2025. In the early years (2010–2014), terms like "database systems," "uncertainty analysis," "communication" and "service-oriented architecture (SOA)" were frequently used to indicate basic work on creating reliable information systems and computational frameworks to support digital agriculture. During the mid-phase (2015–2018), as the focus shifted to apply digital solutions, terms like "cloud computing," "web services," "decision support systems," "learning systems" and "semantics" were commonly utilised. This implies that AI research has focused on decision-making models and service-oriented guidance platforms for agricultural settings. During the consolidation



Figure 1. Tree map of keywords

era (2018–2020), high-frequency terms including "artificial intelligence," "decision making," "machine learning" and "big data" were frequently utilised. This points to a tendency towards intelligent advising systems, data-driven extensions, and predictive analytics. Complex and specialised applications like "deep learning," "artificial neural networks," "internet of things (IoT)," "virtual reality" and "agricultural robots," which demonstrate how cutting-edge AI technologies are integrated into precision farming and immersive extension techniques, were developed during the most recent period (2020–2024). While terminology like "5G mobile communication systems" have evolved to show how next-generation connection enables real-time advising services, terms like "artificial intelligence" and "decision support systems" have persisted for some years, emphasising their critical role in creating the sector. The temporal evolution of keywords indicates a transition from early-stage digital innovations to advanced AI applications aligning with stages of innovation diffusion. This trend reflects the progression from early experimentation to advanced, field-level AI adoption in agricultural advisory services.

Co-occurrence keywords analysis

The co-occurrence keyword network map depicts the interconnected thematic structure of research on artificial intelligence in agricultural extension services, with "artificial intelligence" at the centre and closely linked to "machine learning," "decision making," "decision support systems," "learning systems," and "data mining," all of which form the backbone of AI-driven extension research. Using terms like "decision support systems," "knowledge-based systems," "agricultural robots," "technology adoption," and "sustainable development," the green cluster highlights decision-making and support systems and shows how AI is used to automate services, optimise advisory processes, and connect extension with robotics and sustainability objectives. The blue cluster which includes "information systems," "computer science," "databases," "simulation," "uncertainty analysis," "risk assessment" and "forecasting," highlights the significance of accurate data and predictive modelling while illuminating the computational and infrastructure underpinnings of the field. While the red cluster highlights the digital transformation of agriculture, terms like "digital technologies," "Industry 4.0," "supply chains," "extension services," "5G mobile communication systems" and "optimisation" show how AI is integrated into modern agricultural and communication frameworks. Human-centered and transdisciplinary applications are included in the purple cluster, which connects "deep learning," "virtual reality," "healthcare," "social networking" and "COVID-19." These uses highlight the expansion of immersive technology and cross-sectoral effects. The orange cluster emphasises efforts to make AI-driven systems more user-friendly and flexible for extension delivery by concentrating on accessibility and interoperability through "web services," "semantic web," "ontology," "user interfaces," and "benchmarking." The figure as a whole shows that although the term "artificial intelligence" serves as the discourse's focal point, the field splits into five interrelated streams: computational infrastructure, decision-support applications, agricultural digital transformation, cross-disciplinary innovations, and semantic-web-based user systems. These streams reflect a developing, multidisciplinary, and farmer-centred research landscape. The clustering of technologies and systems suggests interconnected innovation networks that facilitate faster diffusion across agricultural systems. The presence of multiple interconnected clusters indicates that AI-driven extension is not a standalone innovation but part of a broader digital ecosystem, where technological, institutional and socio-economic components interact to shape advisory effectiveness.

Thematic map

The thematic map of research on Artificial Intelligence in agricultural extension services provides a structured overview of

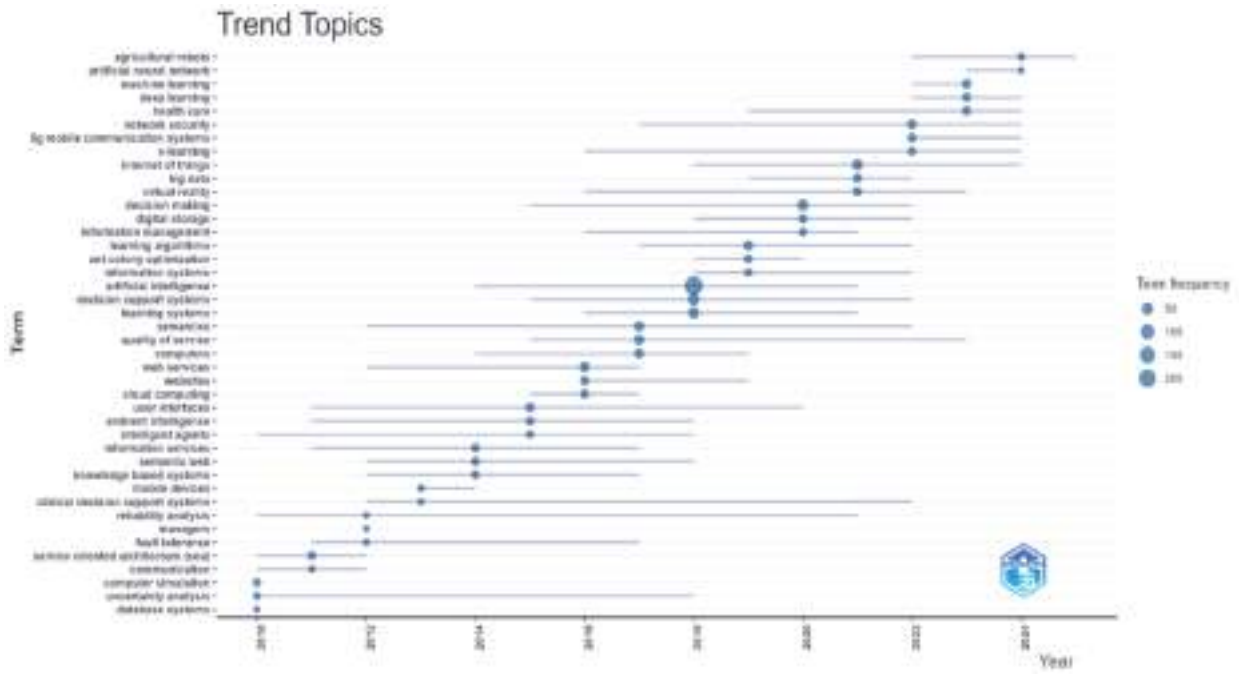


Figure 2. Trend analysis of keywords

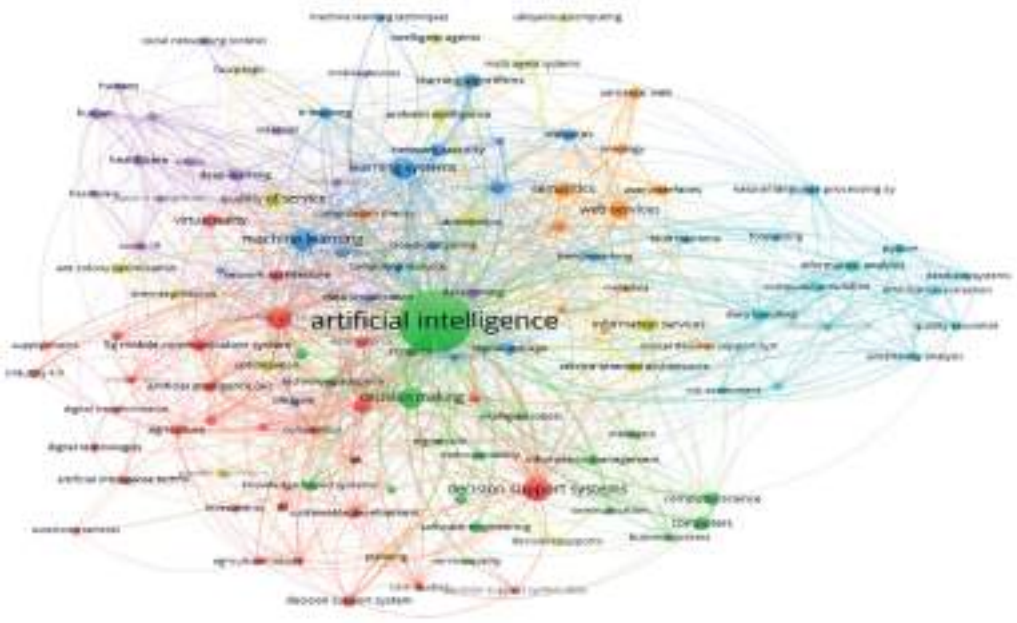


Figure 3. Co-occurrence Network diagram of keywords

how different concepts are positioned in terms of centrality (relevance to the field) and density (degree of development). "Artificial intelligence," "learning systems" and "decision making" stand out as the most fundamental and key ideas in the Basic Themes quadrant (bottom right), acting as the fundamental building blocks that link the whole field of study. The tools and frameworks that support advisory models, farmer decision assistance, and adaptive learning systems are the fundamental core of artificial intelligence in extension. Topics like "ecosystems," "decision support systems," and "sustainable development" seem to be highly developed and important in the Motor Themes quadrant (upper right). Their positioning suggests that they are leading forces in the field, demonstrating how AI is increasingly being used for environmental management, systemic decision-support frameworks that support the UN's sustainability agenda, and more general agricultural sustainability goals in addition to individual advisory tasks. Specialised but less important subjects like "data handling," "information analysis," and "computer simulation" are grouped together in the Niche Themes quadrant (upper left). These are sophisticated, highly developed research fields that provide methodological complexity (e.g., high-resolution data processing and modelling), but their incorporation into mainstream agricultural extension studies is still marginal. "Bayesian networks," "budget control," and "test environment" are included in the Emerging or Declining Themes quadrant (bottom left). Their placement indicates that they are either less well-known than more recent AI-driven techniques or understudied research areas with room to expand (like Bayesian networks in probabilistic modelling). Transitional topics including "deep learning," "healthcare," and "human" are positioned in the middle of the map. Overall, the image shows a clear hierarchy: fundamental AI and decision-making tools serve as the basis, decision-support and sustainability topics propel the field ahead,

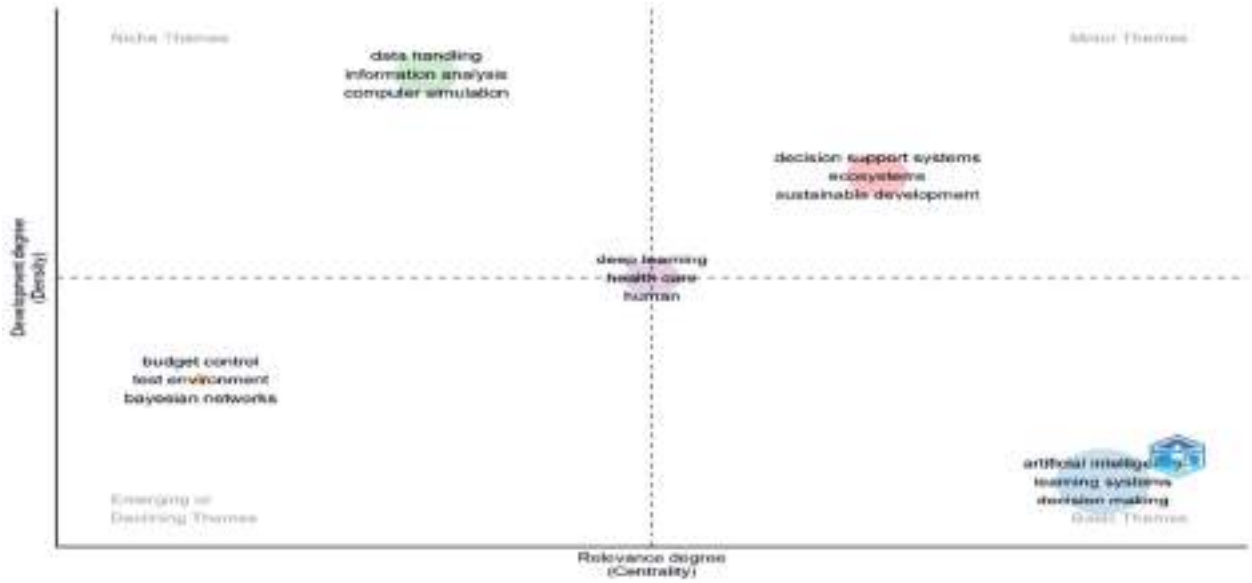


Figure 4. Thematic map

specialised fields enhance the technique and emergent themes suggest future opportunities. This development demonstrates how the discipline is moving from fundamental AI principles to useful, farmer-centered and sustainable applications. The dominance of motor themes such as decision support systems and sustainability indicates that the field is moving toward impact-oriented research, where AI applications are increasingly aligned with global agricultural challenges and policy priorities.

Conceptual structure

The conceptual structure map derived from Multiple Correspondence Analysis (MCA) which explained the thematic organization of the literature on the role of artificial intelligence in enhancing agricultural extension services. The map positioned keywords across two dimensions (Dim 1 and Dim 2) according to their co-occurrence patterns, thereby indicating the conceptual relationships among major research themes. Keywords located closer together represented stronger conceptual associations, whereas those positioned farther apart indicated relatively independent or emerging research directions within the field. The right quadrant of the map was dominated by advanced technological themes such as artificial intelligence, machine learning, deep learning, Internet of Things (IoT), big data and 5G mobile communication systems. The close clustering of these terms suggested that recent studies had largely focused on the integration of intelligent digital technologies into agricultural systems. These technologies were strongly associated with application-oriented concepts such as decision support systems, knowledge-based systems, optimization and sustainable development, indicating that AI-driven analytical tools had been widely explored to improve predictive capabilities, farm-level decision-making, and real-time advisory services delivered through agricultural extension. The central portion of the map included keywords such as knowledge management, data mining, ambient intelligence and decision-making, which functioned as linking domains between technological innovations and extension service outcomes. These themes highlighted the growing importance of managing agricultural knowledge and extracting meaningful insights from large datasets to support evidence-based extension strategies. In contrast, the left side of the map represented foundational information technologies, including the semantic web, distributed computer systems, service-oriented architecture and cloud computing. Overall, the conceptual structure suggested a progressive transition from basic digital infrastructure toward advanced AI-enabled systems designed to enhance the efficiency, accuracy and sustainability of agricultural extension services. This conceptual alignment demonstrates that the field is transitioning from foundational information systems toward advanced AI-enabled knowledge frameworks, emphasizing predictive analytics and data-driven decision-making in extension services.

DISCUSSION

Research on artificial intelligence (AI) in agricultural extension services is a relatively new but quickly developing topic as shown by the bibliometric study of 337 articles from 2010 to 2025. Although average growth has been low (2.33% per year), the sharp increase in production after 2016 suggests a period of significant development, with peaks in 2022 and 2024. Four main topic clusters are identified by the co-occurrence network analysis: institutional and policy frameworks, agricultural systems and innovations, human and environmental factors and adaptive solutions (Roy et

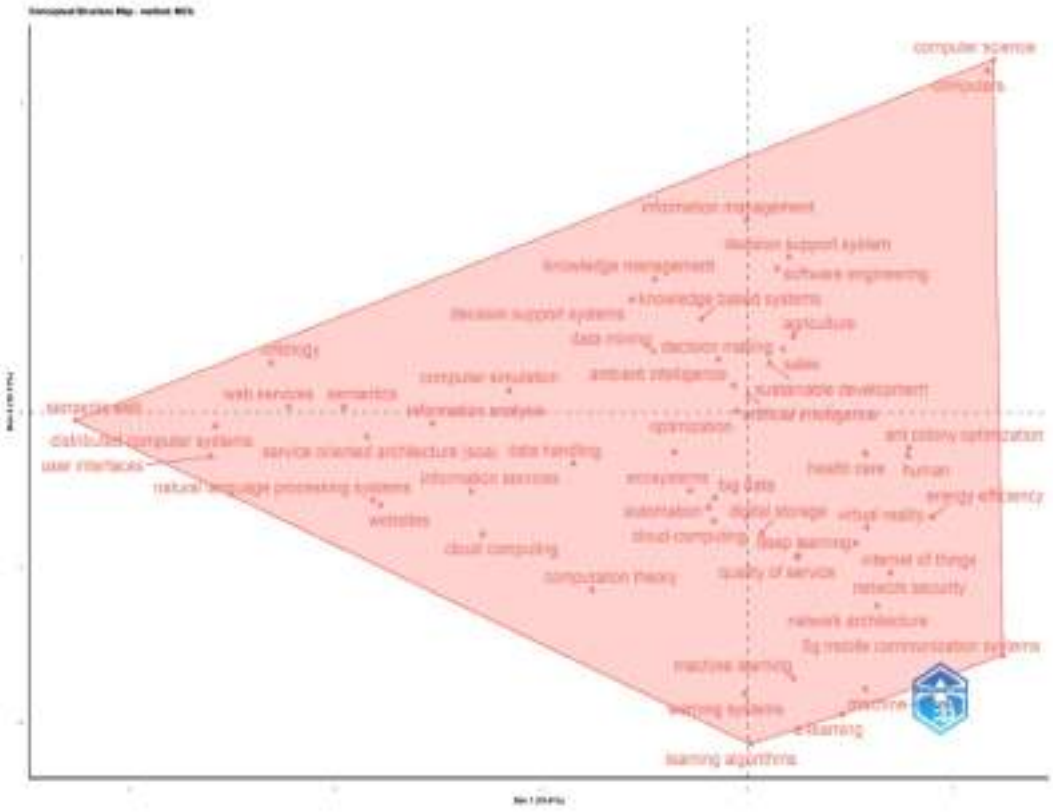


Figure 5. Conceptual Structure Map

al., 2024). According to the bibliometric results, research on AI in agricultural extension has grown consistently since 2010 peaking in 2022 and accelerating significantly after 2016. This path is similar to the global expansion of digital agriculture, where robots, IoT, and machine learning became commonplace topics (Bronson & Knezevic, 2016; Wolfert et al., 2017). Similar multidisciplinary dynamics have been documented in research on ICT4D and precision agriculture where technical complexity necessitates cooperation between domain scientists, policy players and technical specialists (Lioutas & Charatsar, 2019). Large-scale investments in AI infrastructure benefit the US and China, while India's agrarian economy with millions of smallholders makes it an ideal testbed for AI-enabled extension. Despite their smaller amount European donations demonstrate a strong commitment to sustainability and precision farming which is consistent with EU policy aims (Klerkx & Rose, 2024; Barman et al., 2026). A North-South split is shown by the data with many low-income, agriculturally reliant regions particularly in Southeast Asia and Sub-Saharan Africa remaining under-represented while having the greatest need for inclusive extension ideas. Analyses of keyword trends and co-occurrences show a distinct thematic evolution. Infrastructure (database systems, SOA) was the emphasis of early research (2010–2014), which progressively moved to applied digital solutions (learning systems, decision support systems) in the mid-2010s and culminated in frontier applications (virtual reality, deep learning and agricultural robotics) beyond 2020. However, issues like Bayesian networks, budget control, and test environments remain specialist or declining. These trends imply that the two axes of technological sophistication (AI models, IoT integration) and systemic importance (sustainability, ecosystems, farmer decision-making) are stabilising the intellectual structure of AI in extension. Important gaps in our understanding of farmer behaviour, inclusion, and institutional governance are also shown by the bibliometric evidence. Technological tools may not be widely adopted if these socio-institutional factors are not addressed, which is reminiscent of previous experiences when ICTs failed to overcome obstacles related to trust, digital inequality, and local relevance (Aker, 2011). The report draws attention to enduring issues with algorithmic bias, data privacy and digital inequality. AI solutions run the danger of excluding smallholders without cell phones, reliable internet, or digital literacy, even as they offer personalisation at scale. In order to contextualise guidance, foster trust and ensure that technology serves inclusive and location-specific needs, the role of human extension agents remains central, as consistently emphasized in agricultural extension literature. The bibliometric findings further support this perspective, as the co-occurrence network and thematic analysis reveal a strong integration between technological components (machine learning, decision support systems) and extension-related elements such as communication systems, knowledge management and user interfaces. This indicates that AI-driven tools are being developed within existing extension frameworks rather than as independent systems. Therefore, the concept of hybrid extension models is not merely a theoretical assumption but is supported by the observed convergence of technological and human-centred themes, suggesting that effective extension in the AI era will depend on the complementary interaction between digital tools and field-level advisory services (Omotayo et al., 2025).

CONCLUSION

The consistent increase in academic production, especially after 2016 is indicative of a growing understanding of AI's capacity to move extension away from traditional, generalised methods and towards more flexible, data-driven and farmer-specific advising systems. Drawing from computer science, engineering, decision sciences, and the social sciences, the research demonstrates that AI in extension is intrinsically multidisciplinary. The United States, China and India have made significant contributions to the highly collaborative research, but the under-representation of Africa and Latin America reveals a critical imbalance in areas where extension services are most important for rural development and food security. The field's thematic evolution shows a clear trajectory: sophisticated applications like machine learning, deep learning, the Internet of Things (IoT) and immersive technologies have supplanted the early emphasis on digital infrastructure. This suggests that future extension models will rely on the complementary interaction between AI-driven tools and human extension services to ensure effective, inclusive and context-specific advisory delivery.

DECLARATIONS

Ethics approval and informed consent: As the research was carried out with bibliometric analysis, the Scopus database was used for the study, with inclusion and exclusion criteria.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The author declares that they have thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Article

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Training Needs Assessment of Oilseed Farmers for Improved Production Technology in Lucknow District, Uttar Pradesh

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HIGHLIGHTS

- Seed rate and insect pest management were the major areas for training need.
- The majority of farmers prefer the practical training method mainly in their field.
- Farmers prefer May to August or September to December for the training before the time of sowing.
- Method demonstration was most preferred training method for training.

ARTICLE INFO

Keywords: Oilseed, Training Need Index (TNI), TWMS, Method demonstration, Oilseed training programs.

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ABSTRACT

Agriculture plays an important role in India's economic growth, and oilseed crops contribute significantly to nutritional security and farm income. The study was conducted in the Mall block of Lucknow district to assess the training needs of oilseed growers. A total of 125 farmers from five villages were selected randomly for the study, and data were collected through personal interviews with the help of a structured interview schedule. Training needs were analysed using total weighted mean score (TWMS) and the training need index (TNI). The findings revealed that seed rate and insect–pest management were the most needed training areas, followed by field preparation and use of manures and fertilisers. Farmers showed a strong preference for field-based training, with farmers' fields emerging as the most suitable venue (TNI: 88.89%). Morning and the May–December period were identified as the most preferred training times, as the majority of oilseed crops were sown in this period, and farmers need training just before sowing. Among training methods, method demonstration was highly favoured. The study highlights the need-based, location-specific training programs to enhance the adoption of improved oilseed production technologies and increase productivity.

INTRODUCTION

India's vegetable oil economy ranks fourth, after the USA, China, and Brazil (Kaur and Singh, 2023; Tripathi et al., 2023; Bhoi et al., 2026). As oilseeds are the main source of vegetable oil, the residue left over after extraction is high in protein (Lomascolo et al., 2012; Arrutia et al., 2020). Oilseed crops in India are predominantly cultivated under rainfed ecosystems, relying mainly on limited winter showers and conserved monsoonal rainfall (Vaidya et al., 2026). The oilseed sector accounts for 14.3% of the Gross Cropped Area in India, 3% of GNP, and 10% of the value of all agricultural commodities (nmoop.gov.in). Approximately 5–6% of the world's oilseed crop comes from India. In the economic year 2023–2024, approximately 5.44 million tones of oil meals, oilseeds,

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and minor oils were exported, valued at Rs. 29,587 crore. In May 2025, India's oilseed production hit a record high of 42.609 million tones (MT). Approximately 72% of the total oilseed area is cultivated by marginal and small farmers under rainfed conditions (Bhoi et al., 2026). Nine primary oilseed crops make up around 8% of India's agricultural exports, 14.3% of the country's annual gross cultivated land, and 12–13% of its dietary energy. India is the world's top producer of castor, safflower, sesame, and Niger, followed by groundnuts, rapeseed-mustard, linseed, and soybeans (nmeo.dac.gov.in). Global oilseed production is projected to reach a record high of approximately 692 million tonnes in the 2025-26 marketing year, reflecting a 2.2% increase of nearly 15 million tonnes compared to the previous year (Veerapathiran et al., 2025). More than 77% oilseed production in the county comes from the key oilseed producing state of Rajasthan, Madhya Pradesh, Maharashtra, and Gujarat (nmeo.dac.gov.in). In 2022- 2023, India produced 41.35 million tonnes of oilseeds, giving back a significant rise of 3.39 MT as compared to the past year (PIB, 2023). Over the year, the global market for vegetable oils has grown steadily; estimates for 2024-2025 show a 2% increase in production to gain 228 MT[3]. Major improvements in soybean, palm, and rapeseed oil production are anticipated to fuel this growth, with sunflower seed oil output also exhibiting small growth (USDA, 2024). The different agro-climatic regions of the country can support the cultivation of these oilseeds under both rainfed and irrigated farming systems (Meena et al., 2023). The production and productivity of oilseeds differ significantly among the states, with some states leading in the cultivation area and others significantly in terms of production due to higher yield levels (Poornasree & Ponnarasi, 2025). Madhya Pradesh has the largest area under cultivation, totaling 7.29 Mha; Rajasthan (4.97 Mha), Maharashtra (4.58 Mha), Gujarat (2.97 Mha), and Uttar Pradesh (1.20 Mha) came next. With roughly 21.42% of the country's total production, Madhya Pradesh and Rajasthan have the highest production. Despite being a huge producer of oilseed crops in the world, India imports about half of its demand because of a changing lifestyle in dietary patterns and enhanced per capita income (Sarkar et al., 2025). For this study it tried to identify the training needs of farmers regarding the improved production technology of oilseed production practices.

METHODOLOGY

The Study was carried out in the Mall block in the district of Lucknow, during 2019-2020. For the investigation, 5 villages were randomly selected from the Mall block: Imiliha, Sahmau Naubasta, Atri, and Ahinder Aaumau. 25 oilseed growers were selected from each village, for a total of 125 Oilseed growers in the investigation in the study. The Primary Data was collected through direct and personal interviews using pre-tested structured interview schedule from oilseed growers. A 4-point rating scale was used to evaluate the oilseed growers' comments in order to determine their training needs. Most Needed, Needed, Least Needed, and Not Needed by assigning a score of 3,2,1, and 0, respectively, and to assess the Venue of training of farmers in oilseed cultivation practices using 3 continuum scale, Most Prefer, Prefer, and Not Prefer appoint a score of 2,1, and 0, respectively. The total weighted mean score (TWMS) was used to rank each category (Sangameswaran et al., 2022). The rank for perceived training needs was determined by adding the overall weighted mean score, which gave an extensive understanding of their training requirements (Nain & Kumar, 2001; Wason et al., 2012; Singh et al., 2021; Sanarmeswaran et al., 2022; and Patil et al., 2024).

$$TWMS = \frac{\text{Total number of MN+N+LN+NN}}{\text{(No. of MN×3) + (No. of N×2) + (No. of LN×1) + (No. of NN×0)}}$$

Where, NN: Not Needed, LN: Least Needed; N: Needed; MN: Most Needed

Furthermore, Training Needs and place of training of the oilseed growers were calculated based on the Training Need Index (TNI), which was compounded with the help of the following formula (Patil & Kokate, 2011). The TNI method helps quantify the intensity of training needs based on the responses of the oilseed growers.

$$TNI = \frac{\text{Total Obtained Score}}{\text{Maximum Obtained Score}} \times 100$$

Based on the obtained TNI per cent values, the different training areas and training venues were ranked in descending order to determine the priority for organizing a training programme for oilseed farmers.

RESULTS

The findings drawn regarding the determined objectives of the study are based on preferences for place, size of the training group, method, and follow-up activities as recognized by the oilseed growers, using applicable statistical techniques. It has been observed that most farmers showed little interest in training programs; hence, motivational activities should be initiated among farmers through quality input management. The training should emphasize methods of sowing, field preparation, plant protection measures, the use of manures and fertilizers, and post-harvest techniques, as these are the main areas.

The training needs of farmers with regard to oilseed production practices were collected using the Training Need Index (TNI) and the Training Weighted Mean Score (TWMS). The results in Table 1 indicate that the Insects and Pests Management and Seed Rate recorded the highest training needs, with TWMS of 0.341 and TNI

Table 1. Training Needs of Farmers in Oilseed Production Practices

Training Needs Area	Degree of Training Needs		
	Mean Score	TWMS*	TNI (%)**
Insects and Pests Management	2.93	0.341	97.78
Seed Rate	2.93	0.341	97.78
Field Preparation	2.82	0.355	93.89
Use of Manures and Fertilizers	2.78	0.359	92.78
Method of Sowing	2.60	0.385	86.67
Seed Treatment	2.45	0.408	81.67
Disease management	2.38	0.42	79.44
Weed Management	2.35	0.426	78.33
Harvesting	2.27	0.441	75.56
Post-Harvest technology	2.00	0.500	66.67

** TNI: Training Need Index *TWMS: Total Weighted Mean Score

of 97.78%, acquire first place. Field Preparation ranked second with a mean score of 2.82 and TNI of 93.89 per cent, followed by use of manures and fertilisers, which ranked third with a TWMS of 0.359 and TNI of 92.78 per cent.

The training need for the Method of Sowing was moderate, with a TWMS of 0.385 and a TNI of 86.67 per cent, placing it at the fourth rank. Followed by Seed Treatment, ranked fifth with a TWMS of 0.408, TNI of 81.67%, Weed Management was ranked seventh with a mean score of 2.35 and TNI of 78.33%, Disease Management secured the sixth rank with a TWMS of 0.420 and a TNI of 79.44%, Harvesting secured the eighth rank with a TWMS of 0.441 and TNI of 75.56 per cent, and the least training need was observed in Post-Harvest Technology, which obtained a TWMS of 0.500, and a TNI of 66.67 per cent, ranking ninth rank.

The results in Table 2 indicate that Farmers' Field was perceived as the most preferred venue for training, securing first place with TWMS of 0.56 and TNI of 88.89%. Followed by Village School, which was ranked second (TWMS of 0.58 and TNI of 86.11%), Village Panchayat secured the third rank (TWMS 0.60 and TNI of 83.33%), Block Headquarters ranked fourth (TWMS 0.77 and TNI of 65.00%), and Degree College received a lower preference, securing the fifth rank with a TWMS of 1.58 and TNI of 31.67%, and Research Farm, which ranked sixth with a TWMS of 2.14 and TNI of 23.33%.

Table 2. Place of training of Farmers in Oilseed Production Practices

Venue of Training	Venue Preference		
	Mean Score	TWMS*	TNI % **
Farmers Field	1.78	0.56	88.89
Village School	1.72	0.58	86.11
Village Panchayat	1.67	0.60	83.33
Block Headquarters	1.30	0.77	65.00
Degree College	0.63	1.58	31.67
Research Farm	0.47	2.14	23.33

** TNI: Training Need Index *TWMS: Total Weighted Mean Score

Table 3 shows that most of the oilseed growers (62.40%) preferred that training on oilseed production technology be conducted in the morning hours of the day, while only (09.60%) of the farmers prefer training to be conducted at any time of the day.

Table 3. Oilseed growers' preferences for the time of training

Time of Training	Frequency	Percentage
Preference for the time of the Day		
Morning	78	62.40
Afternoon	20	16.00
Evening	15	12.00
Any time of day	12	09.60
Preferences for training day of the week		
Sunday	17	13.60
Saturday- Sunday	32	25.60
Any day	76	60.80
Preferences for the month of the year		
May to August	73	58.40
September to December	52	41.60

The table also shows that most farmers prefer any day (60.80%) of training, followed by Saturday and Sunday (25.60%), and only Sunday (13.60%) of training. Whereas most of the farmers (58.40%) preferred that may to august month of the training, and (41.60%) of farmers preferred September to December month of training. Other months of years not preferred by the farmers for training.

From various methods of extension teaching (Table 4) majority of farmers prefer Method demonstration (92.00%) was the most preferred training method among the oilseed growers, followed by result demonstration (86.40%), and field visit (71.20%), Group Discussion (65.00%), On-farm trials (57.60%) whereas, Printed literature and Video Lecture were the least preferred methods of training.

Table 4. Preference Training Methods

Training Methods	Percentage
Method Demonstration	92.00
Result Demonstration	86.40
Field Visit	71.20
Group Discussion	65.00
On-farm trials	57.60
Lecture	48.00
Printed literature	44.00
Video Lecture	46.40

DISCUSSION

The findings on the Training Needs of farmers for oilseed production technology revealed that seed rate and insect and pest management were the most important training needs, with the highest TNI (97.78%) and lowest TWMS (0.341), thereby securing the top rank similar study was found in (Barman et al., 2013). This suggests that farmers are not sufficiently informed about the optimal seed rate and efficient insect and pest management practices, both of which are important determinants of oilseed crop productivity (Rathore et al., 2019). The growing challenges posed by pest incidence, climate variability, and inappropriate pesticide use, which call for focused extension interventions, are also reflected in the prominence of pest management as a training need.

The selection of a suitable training venue has a significant impact on farmers' effectiveness, participation, and knowledge retention. The results show that Farmers 'Field (TNI: 88.89% and TWMS: 0.56) was the most preferred venue for conducting the training programme (Tankodara et al., 2019). Farmers' preferences toward experiential learning environments, field-based, where they can directly perceive and highlight enhanced oilseed production techniques in actual fields, are highlighted by this strong preference. Such environments enable higher adoption rates, which improve the contextual relevance, immediate application, and practical comprehension (Nain & Trikha, 2009; Tamlinson & Rhiney, 2018).

The triumph of oilseed production technology training programs greatly depends on how effectively they work with farmers' schedules and available work hours. These are all principal components that influence learning outcomes and participation. Based on the results, the majority of oilseed farmers (62.40%) would prefer the morning time of training. 16 per cent of farmers prefer

to have it in the afternoon, and 12 per cent of farmers prefer it in the evening of training (Abebe et al., 2022). Farmers were typically more attentive, active, and accessible before they started their regular work in agriculture, which typically gets busier later in the day, which could explain their strong preference for morning sessions. By lowering weariness and improving comprehension, morning sessions generate a positive learning environment. Farmers are open to flexible scheduling as long as the training is beneficial and accessible, as evidenced by the 60.80% of them who stated they would be okay with any day of instruction. This indicates that some farmers are more willing to engage because they have less labour to perform or find it easier to work on the weekends. The range of responses indicates that flexibility is possible, but knowledgeable scheduling that considers labour requirements and local farming schedules is required. In case of periodic preference, the majority of oilseed farmers (58.40%) choose training from May to August (Srivastava & Shrivastava, 2023). This indicates that farmers favour training during specific phases of the agricultural cycle, particularly when they can immediately apply the knowledge they have acquired to crop production processes. Since most oilseed crops are sown between May and August and September and December, the oilseed growers primarily select these seasons for oilseed production training. The early stages of crop growth and preparation, when decisions about crop management, input use, and sowing are essential, may also correlate with the oilseed growers' desire for training in advance of sowing. Different researches reported context-specific preferences for different aspects of training (Kher et al., 2004; Bhagat & Nain, 2005; Kumar et al., 2007; Nath et al., 2025)

The study found that technique demonstration was the most widely used training technique among oilseed growers (92.00%) (Husin et al., 2026). This highlights the need of experiential learning, where farmers may observe and apply improved farming practices directly. This method speeds up the adoption of new technologies, increases confidence, and improves skill acquisition. Result demonstration (86.40%) was also strongly favoured, suggesting that farmers place a high importance on observable results and the relative benefits of better practices over conventional ones. This supports the idea that when farmers can clearly see the advantages of innovations in actual field settings, they are more likely to adopt them (Yadav et al., 2025).

CONCLUSION

The study concluded that oilseed growers show significant training needs, particularly in seed rate and insect-pest management, which ranked highest based on TNI and TWMS values. Other important areas include field preparation and the use of manures and fertilizers, showing gaps in essential crop management practices. Farmers showed a strong liking toward practical and field-oriented learning, with farmers' fields identified as the most preferred training venue. Morning hours and the May–December period were found to be most suitable for organizing training programs, to secure better participation. Among training methods, method demonstration and result demonstration were highly preferred, highlighting the importance of experiential learning approaches.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the respondents and their organisations regarding the study during the course of the data collection.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The author declares that they have thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Article

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Economic Contribution of Non-Timber Forest Products to Rural Livelihoods in the Shivalik Range of Jammu and Kashmir

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HIGHLIGHTS

- Non-Timber Forest Products (NTFPs) contributed 29% of the total annual household income.
- Households engaged in NTFP collection often travelled long distances up to 25.69 km/day and dedicated multiple weeks per year to gathering resources.
- Regression analysis indicated that NTFP availability, collection experience, and agriculture as the main occupation positively influenced income from NTFPs.

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ABSTRACT

This research was carried out to examine the importance and economic value of identified Non- Timber Forest Products (NTFPs) in supporting the livelihoods of forest dwellers East Forest Circle of Jammu and Kashmir. The NTFPs were identified and documented with the help of participatory rural appraisal methods. Multi-stage random sampling method was used to identify the ultimate sampling units. The study revealed that NTFP income contributed 29%, on-farm 16% and off-farm 55% of total household income. It was found that ten NTFPs, were collected by the forest dwellers which significantly contributed to their livelihoods. By applying regression analyses, it was found that NTFP availability, agricultural occupation, NTFP collection experience and on-farm-income had a positive impact on NTFP income. From the research, it was recommended to teach and organize capacity building programs for the forest dwellers in order to improve their level of competence in NTFP collection, storage and grading.

INTRODUCTION

Forests have long played a crucial role in sustaining human livelihoods by providing a wide range of goods and ecosystem services that support both economic and socio-cultural needs. Among these, Non-Timber Forest Products (NTFPs) are defined as all biological materials other than timber extracted from forests are particularly significant for rural and forest-dependent communities (Vantomme, 2003; Forestry). NTFPs include a diverse array of products such as medicinal plants, fruits, fodder, resins, fibres, and fuelwood, which are essential for subsistence as well as income generation.

Globally, it is estimated that nearly 1.6 billion people depend on forest resources for their livelihoods, with a substantial proportion relying on NTFPs for food security, healthcare, and income (Derebe et al., 2023). In developing countries, more than 80 per cent of the population depends on plant-based resources derived from forests for nutritional and medicinal purposes (Nautiyal & Kaul, 2003; Duong, 2008). These products serve as a critical safety net, particularly for economically marginalized

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communities, by providing supplementary income during periods of agricultural uncertainty (Ibrahim et al., 2020; Tiwari et al., 2022). In many regions of Asia and Africa, NTFPs contribute significantly to household economies and play a vital role in sustaining traditional knowledge systems and cultural practices (Arnold et al., 2011; Sills et al., 2003; Belem et al., 2007).

In the Indian context, NTFPs form an integral component of rural livelihoods, especially among tribal and forest-dependent populations. The annual contribution of NTFPs to the Indian economy is estimated to be approximately USD 2.7 billion, supporting more than 55 per cent of employment in the forest sector. Nearly one-third of the rural population in India derives a portion of their household income from NTFPs (Sharma, 2019; Ahmad et al., 2021). These products not only provide direct economic benefits but also contribute to livelihood diversification, risk reduction, and resilience against climate and market shocks (Gupta et al., 2023; Pathania & Negi, 2022).

The Union Territory of Jammu and Kashmir possesses rich forest resources, covering approximately 20,230 square kilometers, which constitutes about 20 per cent of its total geographical area. In this region, NTFPs serve as a vital livelihood strategy, particularly for landless households and economically weaker sections. Forest dwellers depend on these resources for subsistence needs such as food, medicine, and fuel, as well as for generating cash income through market channels. Despite their importance, the economic contribution of NTFPs is often undervalued due to inadequate documentation, lack of organized markets, and limited policy support.

Although several studies have examined the role of NTFPs in livelihood security across different regions of India, there is a notable research gap concerning the Shivalik range of Jammu and Kashmir. Existing literature largely focuses on other states such as Himachal Pradesh, Chhattisgarh, and Tamil Nadu, with limited empirical evidence available for the Jammu region. Furthermore, the socio-economic determinants influencing NTFP dependence and income generation remain underexplored in this specific geographical context.

METHODOLOGY

The study was conducted in the East Forest Circle of Jammu and Kashmir, which encompasses diverse agro-climatic zones, namely subtropical, intermediate, and temperate regions. The area is characterized by rich forest biodiversity and significant dependence of local communities on forest resources, particularly Non-Timber Forest Products (NTFPs), for subsistence and income generation. The East Forest Circle comprises seven forest divisions, providing a suitable setting to examine variations in NTFP availability and utilization. A multistage sampling design was employed to ensure representativeness of the study area. In the first stage, three forest divisions Basholi, Ramnagar, and Udhampur were selected from the total seven divisions using a simple random sampling technique without replacement. In the second stage, forest ranges, blocks, and beats with relatively higher NTFP collection activities were identified in consultation with forest department officials. This purposive selection at intermediate stages was necessary due to the absence of a comprehensive sampling frame of NTFP collectors. At the final stage, NTFP collectors were selected as the ultimate sampling units. Since no official records of collectors were available, a snowball sampling technique was adopted. The initial respondents were identified with the help of local resource persons and forest officials, and subsequent respondents were contacted through referrals. A total of 150 NTFP collectors were surveyed, with 50 respondents selected from each of the three forest divisions. The sample size was considered adequate to capture variability in socio-economic characteristics and NTFP dependence across the study area. Primary data were collected during the agricultural year through personal interviews using a structured and pre-tested interview schedule. Secondary data were obtained from published literature, government reports, and forest department records to supplement the primary findings. Household income was categorized into three major components viz; on-farm income (income derived from agricultural and allied activities); off-farm income (income from wage labor, services, and other non-agricultural sources) and NTFP income (income generated from the collection and sale of non-timber forest products). The total household income was computed as the sum of these three components.

Total household income = Σ(On-farm income + Off-farm income + NTFPs income)

The collected data were coded and analyzed using Microsoft Excel (2010) and SPSS (Version 18). Both descriptive and inferential statistical techniques were employed. Descriptive statistics such as mean, percentage, standard deviation, and frequency distribution were used to analyze: patterns of NTFP collection and utilization; income distribution across different livelihood sources; contribution of individual NTFPs to household income. To identify the socio-economic factors influencing NTFP income, an Ordinary Least Squares (OLS) regression model was employed. The model specification is as follows:

$$Y = \beta_0 + \Sigma\beta_i X_i + u$$

Where, Y= Income derived from NTFPs, β_0 = Intercept, β_i = Coefficients of explanatory variables, X_i = Socio-economic characteristics of households (e.g., NTFP availability, occupation, experience, income sources), *u* = Error term, The regression model was used to estimate the direction and magnitude of influence of explanatory variables on NTFP income.

RESULTS

The utilization of Non-Timber Forest Products (NTFPs) in the study area was influenced by several factors, including resource accessibility, species diversity in nearby forest ecosystems, and market availability. However, the pattern of utilization varied considerably across locations and among households within the same community, reflecting differences in resource availability and livelihood strategies.

The findings presented in Table 1 indicate that a majority of respondents depend on forests for basic subsistence needs such as fodder and fuelwood collection. Approximately 63 per cent of the respondents reported collecting fodder for livestock, with an average travel distance of 4.43 ± 3.69 km from their residences. Similarly, fuelwood collection was practiced by 86 per cent of the respondents, who travelled an average distance of 6.74 ± 2.29 km.

Table 1. Status of collection of fodder and fuel wood from the forests

Parameter	Total (n=150)
Fodder	63
Distance travelled (km)	4.43±3.69
Fuelwood	86
Distance travelled (km)	6.74±2.29

The relatively higher engagement in fuelwood collection, along with the greater distance travelled, suggests a stronger and more consistent dependence on forest resources for energy requirements, highlighting the critical role of forests in sustaining rural livelihoods in the region.

The workforce characteristics of the sampled households are presented in Table 2. The total family size of the 150 sampled households was 903 members, of which 66 per cent constituted adult members, while 38 per cent were actively engaged in income-generating activities. The dependency ratio was estimated at 1:2.96, indicating a relatively high burden on earning members. The findings further reveal that only 3 per cent of the households were solely dependent on Non-Timber Forest Products (NTFPs) for their livelihood, while none of the households relied exclusively on farming. A majority (97%) of the households exhibited diversified livelihood strategies, combining NTFP collection with other income sources. Among these, wage labour emerged as the dominant source of income (64%), followed by private employment (9%) and a combination of labour and private jobs (9%). A smaller proportion of households were engaged in business activities such as shopkeeping (6%), while others combined labour with government service (2%) or other minor occupations (3%). These findings indicate that forest-dependent households in the study area rely heavily on livelihood diversification, with NTFPs serving as a supplementary rather than a primary source of income.

Table 2. Workforce status of respondents' household

Parameter	Total (n=150)
Total family members	903
Total number of adults (% farmers)	66
Total number of earning members (off- farm activities) (% farmers)	38
Dependency ratio (off- farm activities)	1:2.96
Households solely dependent on NTFP income (% farmers)	3
Households solely dependent on faming	0
Households having other sources of income including NTFP and Agriculture	97
Labour	64
Private	9
Shop	6
Labour + Government service	2
Labour + Shop	4
Labour + Private	9
Government service	0
Any other	3

The results (Table 3) reveal substantial variation across different NTFPs in terms of collection duration, quantity harvested, distance travelled, participation patterns, and marketing channels. Among the identified NTFPs, *patis* (*Aconitum chasmanthum*) and *gucchi* (*Morchella esculenta*) were the most commercially significant products. Collection of *patis* involved relatively long travel distances (25.69 ± 8.07 km per day) and was entirely group-based, with an average group size of 2.67 ± 1.23 persons. Collectors participated in this activity for about 28.69 ± 10.99 days annually, harvesting an average of 10.79 ± 8.85 kg per household, all of which was sold through agents. Similarly, *gucchi* collection required moderate travel distances (14.97 ± 6.62 km per day) and longer participation (33.25 ± 11.72 days annually). Unlike *patis*, *gucchi* collection exhibited both individual (56%) and group-based (44%) participation. The entire harvested quantity (1.27 ± 1.11 kg per household) was also marketed through intermediaries.

In contrast, *kasrot* (*Diplazium esculentum*) demonstrated a mixed subsistence and commercial role. Although collectors harvested relatively large quantities (115.37 ± 297.75 kg), only a portion (49.30 ± 16.58 kg) was sold, primarily through local shops, while the remaining was consumed domestically. The collection of

Table 3. Collection and marketing of NTFPs

Parameter	Patis (n=103)	Gucchi (n=148)	Kasrot (n=20)	Bnafsaha (n=48)	Nag chhatri (n=104)	Kaud (n=35)	Dhoop (n=48)	Mushkbala (n=84)	Zakham-e-hiyat (n=32)
Number of collection days	28.69 ±10.99	33.25 ±11.72	17.31 ±9.48	43.19 ±11.35	33.95 ±10.90	18.73 ±3.62	15.89 ±8.77	23.63 ±6.36	7.50 ±2.47
Quantity collected (kg)	10.79 ±8.85	1.27 ±1.11	115.37 ±297.75	0.28 ±0.16	16.16 ±16.98	18.53 ±27.89	26.18 ±20.29	30.71 ±21.08	45.93 ±12.14
Quantity sold (kg)	10.79 ±8.85	1.27 ±1.11	49.30 ±16.58	0.28 ±0.16	16.16 ±16.98	18.53 ±27.89	26.18 ±20.29	30.71 ±21.08	45.93 ±12.14
Quantity consumed (kg)	0	0	67.89 ±217.07	0	0	0	0	0	0
Distance (km)	25.69 ±8.07	14.97 ±6.62	6.30 ±4.24	18.22 ±5.21	27.19 ±8.42	17.94 ±4.10	28.53 ±10.79	10.03 ±5.07	11.47 ±4.43
Collected Individually (%)	0	56	100	22	0	0	5	27	22
Collected in Groups (%)	100	44	0	78	100	100	95	73	78
Number of persons in group	2.67 ±1.23	2.48 ±1.35		2.69 ±0.78	2.97 ±1.09	2.70 ±0.90	2.7 ±2.03	2.67 ±0.78	2.20 ±0.41
Sold to Local shops	0	27	100	0	0	0	0	0	0
Sold to Agents	100	73	–	100	100	100	100	100	100

kasrot involved shorter travel distances (6.30 ± 4.24 km) and was carried out individually. Other NTFPs, including *banafsaha* (*Viola odorata*), *nag chhatri* (*Trillium govanianum*), *kaud* (*Picrorhiza kurroa*), *dhoop* (*Jurinea macrocephala*), *mushkbala* (*Valeriana jatamansi*), and *zakham-e-hayat* (*Bergenia ciliata*), exhibited varying collection patterns. These products were largely collected in groups, with participation ranging from 73 to 100 per cent. The duration of collection varied from 7.50 to 43.19 days annually, while travel distances ranged between 10.03 and 28.53 km per day. In most cases, the entire quantity collected was sold through agents, indicating a strong reliance on intermediary-based marketing systems. Overall, the findings highlight that NTFP collection in the study area is labor-intensive, often involving long travel distances and group participation. High-value NTFPs such as *patis* and *gucchi* are predominantly commercial in nature, whereas others like *kasrot* serve both subsistence and income-generating functions. The dominance of agent-based marketing further reflects limited direct market access for collectors.

The distribution of household income from different sources is presented in Table 4. The results indicate that the average annual household income of the sampled NTFP collectors was Rs. 173,650 ± 120,575. Among the various income sources, off-farm income constituted the largest share, with an average of Rs. 110,440 ± 110,438, accounting for 55 per cent of the total household income.

In comparison, income from NTFPs contributed an average of Rs. 58,584.40 ± 49,705.70, representing 29 per cent of total household income. On-farm income was relatively lower, averaging Rs. 31,773 ± 19,486.40, and contributed 16 per cent to the total income. These findings indicate that while off-farm activities remain the primary source of livelihood, NTFPs play a significant supplementary role in supporting household income among forest dwellers in the study area.

The results indicate that *patis* (*Aconitum chasmanthum*) contributed the highest share (32.04%) to total NTFP income, followed by *gucchi* (*Morchella esculenta*) (26.49%) and *nag chhatri* (*Trillium govanianum*) (15.77%). Together, these high-value NTFPs accounted for a substantial proportion of total income derived from forest resources (Table 5). Moderate contributions were observed from *banafsaha* (*Viola canescence*) (9.46%), *kaurd* (*Picrorhiza kurroa*) (5.22%), *dhoop* (*Jurinea macrocephala*) (4.63%), and *mushkbala* (*Valeriana hardwickii*) (4.03%). In contrast, products such as *kasrot* (*Diplazium esculentum*) (1.13%), wild honey (0.65%), *zakham-e-hayat* (*Bergenia ciliata*) (0.35%), and *jungli thome* (*Allium sativum*) (0.16%) contributed marginally to household income. In terms of household participation, *gucchi* collection showed the highest engagement (99%), followed by *patis* and *nag chhatri* (69% each), indicating their widespread economic importance. Other NTFPs exhibited relatively lower participation levels, reflecting variation in resource availability, market demand, and collection feasibility. Overall, the findings suggest that a limited number of high-value NTFPs dominate income generation, while several others play a supplementary role, highlighting the uneven distribution of economic benefits across different forest products.

Factors driving households for collection of NTFPs

The relationship between household characteristics (independent variables) and the percentage share of NTFP income (dependent variable) was analyzed using a regression model. The results presented in Table 6 indicate that all five predictors were significant and played an important role in determining the dependent variable. Among these, NTFP availability, experience in NTFP collection, and occupation as a farmer showed a positive influence on NTFP income share. In contrast, off-farm income and source of information exhibited a negative relationship with NTFP income.

These findings are in line with the results reported by Sharma (2015), who observed that socio-economic factors such as landholding, literacy index, and age of the household head significantly influence dependence on NTFPs in Himachal Pradesh. The study highlighted that households with smaller landholdings

Table 4. Source of income of sampled households

Type of Income	Average annual income (Rs)	Standard error	Income share (%)
Average annual off farm income	110440.00±110438	7.51	55
Average annual on farm income	31773.00±19486.40	1.59	16
Average annual NTFP income	58584.40±49705.70	4.06	29
Average annual household income	173650.00±120575	9.94	

Table 5. Contribution of various NTFPs to cash income

NTFPs	Average annual income per household (Rs)	Per cent of households engaged
Dhoop (*Jurinea macrocephala*)	8472.92±5537.87	32
Gucchi (*Morchella esculenta*)	15626.38±16000.72	99
Kasrot (*Diplazium esculentum*)	4422.63±3425.71	13
Banafsaha (*Viola canescence*)	12224.26±7577.23	32
Wild honey	14375.00±6574.89	3
Patis (*Aconitum chasmanthum*)	27339.81±16132.15	69
Nag chhatri (*Trillium govanianum*)	13198.1±8745.12	69
Kaurd (*Picorhiza kurroa*)	13497.06±19366.88	23
Junglithome (*Allium sativum*)	14000.00	1
Muskbala (*Valeriana hardwickii*)	4215.48±2389.06	56
Zakham-e- hiyat (*Bergenia ciliata*)	962.50±268.56	21

Table 6. The socio-economic variables determining the cash income generated by the households from NTFP collection

Model	Coefficients	Standard error	t-value	Significance
(Constant)	8.89	4.72	1.88*	0.06
NTFP availability (X_{17})	1.81	0.32	5.69***	0.01
R^2	0.18	Adjusted R^2		0.17
(Constant)	19.41	4.81	4.04***	0.01
NTFP availability (X_{17})	1.61	0.29	5.40***	0.01
Off-farm income (X_{14})	-6.87	0.00	-5.15***	0.01
R^2	0.30	Adjusted R^2		0.29
(Constant)	9.64	5.36	1.79*	0.07
NTFP availability (X_{17})	1.48	0.28	5.14***	0.01
Off-farm income (X_{14})	-6.98	0.00	-5.44***	0.01
NTFP collection experience (X_5)	0.67	0.18	3.61***	0.01
R^2	0.36	Adjusted R^2		0.35
(Constant)	6.48	5.38	1.20NS	0.23
NTFP availability (X_{17})	1.72	0.29	5.80***	0.01
Off-farm income (X_{14})	-6.92	0.00	-5.50***	0.01
NTFP collection experience (X_5)	0.59	0.18	3.18***	0.01
Occupation (X_9)	14.21	5.35	2.65***	0.01
R^2	0.39	Adjusted R^2		0.37
(Constant)	33.39	12.46	2.68***	0.01
NTFP availability (X_{17})	1.72	0.29	5.87***	0.01
Off-farm income (X_{14})	-6.76	0.00	-5.45***	0.01
NTFP collection experience (X_5)	0.55	0.18	2.96***	0.01
Occupation (X_9)	15.22	5.28	2.88***	0.01
Source of information (X_{10})	-4.17	1.75	-2.38***	0.01
R^2	0.41	Adjusted R^2		0.39

*** and * Significant at one and 10 per cent levels, NS: Non-significant

tend to rely more on NTFPs, whereas those with larger landholdings show relatively lower dependence. Similarly, households with lower literacy levels were found to be more dependent on NTFP collection compared to those with higher literacy levels. Furthermore, older household members possess greater knowledge of economically valuable NTFPs, thereby increasing reliance on forest resources among experienced households.

The adjusted R^2 values indicate a progressive increase in the explanatory power of the model with the inclusion of additional variables. NTFP availability alone explained 17 per cent of the variation in NTFP income share. When off-farm income was included, the explained variation increased to 30 per cent. Further inclusion of NTFP collection experience increased the explanatory power to 35 per cent. Similarly, the addition of occupation as the main source of livelihood raised it to 37 per cent, while the inclusion of source of information resulted in a final explanatory power of 39 per cent. The OLS estimates indicate that a unit increase in NTFP availability (X_{17}) leads to a 1.72 unit change in NTFP income share. Conversely, a unit decrease in off-farm income (X_{14}) results in a 6.76 unit increase in NTFP income share. Similarly, a unit increase in NTFP collection experience (X_5) and agriculture as the primary occupation (X_9) increases NTFP income share by 0.55 and 15.22 units, respectively. In contrast, a unit increase in the source of information (X_{10}) reduces NTFP income share by 4.17 units. Easily availability of NTFPs was found to be the main reason for collection as it was reported by all the collectors and was ranked number one. Source of income, to meet food requirement and profitable activity were reported by 95, 93 and 88 per cent of the collectors (Table 7).

Table 7. Reasons for collection of NTFPs

Parameter (% Collectors)	Total (n= 150)
Source of income	95
Profitable activity	88
To meet food requirement	93
Available nearby	100

DISCUSSION

Forest-dependent households residing in and around forest areas rely extensively on Non-Timber Forest Products (NTFPs) as an integral component of their livelihood strategies. The collection and utilization of NTFPs have traditionally supported both subsistence needs and income generation among forest dwellers. These products not only provide direct consumption benefits but also contribute to household income through market sales, thereby enhancing food security by improving purchasing capacity. The findings of the present study indicate that households in the study area adopt a diversified livelihood strategy rather than depending on a single source of income. Among the three major income sources–NTFPs, on-farm, and off-farm activities–off-farm income emerged as the dominant contributor, accounting for 55 per cent of total household income. A large proportion of respondents were engaged in wage labour (65%), reflecting limited agricultural opportunities and the increasing importance of non-farm employment. NTFPs constituted the second most important source of income, contributing 29 per cent, followed by on-farm income (16%). These findings are consistent with earlier studies, which

reported NTFP contributions of 17 per cent in West Bengal (Malhotra et al., 1991), 24 per cent in Tamil Nadu (Ganesan, 1993), and 21 per cent in Sri Lanka (Gunatilke et al., 1993), indicating the continued relevance of NTFPs in rural livelihoods across regions.

Although a variety of NTFPs are collected in the study area, only a limited number contribute significantly to household income. Among these, *patis* (*Aconitum chasmanthum*) and *gucchi* (*Morchella esculenta*) were the major contributors, reflecting their high market value and demand. This pattern aligns with previous studies (Kant, 1997; Paloti & Hiremath, 2005; Pervez, 2002; Kanwal, 2014; Tejaswi, 2008; Choudhary, 2023), which also reported that only a few high-value NTFPs dominate income generation. Furthermore, the role of rural women in NTFP collection and processing was found to be substantial, indicating the gendered nature of forest-based livelihoods. The regression analysis further revealed that NTFP dependence is significantly influenced by socio-economic factors. Variables such as NTFP availability, collection experience, and agriculture as the primary occupation showed a positive association with NTFP income, suggesting that resource accessibility and household capabilities enhance dependence on forest products. In contrast, off-farm income and access to information exhibited a negative relationship with NTFP dependence, indicating that households with diversified income sources and better information access tend to rely less on forest resources. These findings are in agreement with Sharma (2015), who reported that landholding size, literacy level, and age of the household head significantly influence dependence on NTFPs. Households with limited land resources and lower literacy levels were found to be more dependent on forest-based livelihoods, whereas experienced household members possessed better knowledge of commercially valuable NTFPs, leading to higher engagement in collection activities. Overall, the study highlights that NTFP dependence is shaped by a complex interplay of resource availability, socio-economic conditions, and livelihood diversification. While NTFPs continue to play a vital supplementary role, the increasing importance of off-farm income suggests a gradual shift towards diversified livelihood strategies among forest-dependent households.

CONCLUSION

The household livelihoods in the study area are supported by a combination of on-farm, off-farm, and Non-Timber Forest Products (NTFPs)-based income sources. Among these, off-farm income emerged as the dominant contributor, accounting for 55 per cent of total household income, followed by NTFPs (29%) and on-farm income (16%). Households engage in NTFP collection for multiple purposes, including consumption and commercial sale, indicating their dual economic and socio-cultural importance. Capacity-building initiatives focusing on scientific methods of collection, storage, grading, and value addition are essential to enhance income from NTFPs. Furthermore, strengthening backward and forward linkages such as improved transportation, storage facilities, processing units, and market access can help ensure better price realization and product quality. There is a need for increased awareness and sensitization regarding the economic and ecological value of NTFPs, along with institutional support to promote sustainable harvesting practices.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the respondents and their organisations regarding the study during the course of the data collection.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The author declares that they have thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Article

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A Study on Aspiration of Farm Youth towards Agriculture in Rayagada District of Odisha

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HIGHLIGHTS

- Age, farming experience, innovative proneness, risk orientation, farming commitment, and economic motivation influence youth aspiration towards agriculture.
- Path analysis indicates age, experience, landholding, family size, and innovativeness show strongest direct effects on overall aspiration.
- Youth-focused interventions should emphasize experiential learning, extension, and effective communication strategies to enhance aspiration and agricultural engagement.

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ABSTRACT

The study examined the aspiration of farm youth towards agriculture in Rayagada district of Odisha during 2023–2024 and identified the variables influencing their involvement in farming. The main objective was to estimate the level of aspiration of farm youth and to analyze the personal, economic, and psychological factors affecting it. In this regard, an ex-post facto type of research design was used in which a sample of 150 farm youths was randomly drawn from ten villages located in two blocks. Primary data were collected through personal interviews using a structured schedule. Correlation analysis found that age and farming experience among personal factors, family income among economic factors, and innovative proneness, risk orientation, farming commitment, and economic motivation among psychological factors were positively and significantly associated with aspiration. Multiple regression analysis revealed that education, innovative proneness, farming commitment and farming experience had significantly contributed towards aspiration. Path analysis indicated that age, farming experience, landholding, family size, and innovative proneness exerted the highest direct effects on aspiration, while economic motivation, extension contact, mass media use, and cosmopoliteness contributed mainly through indirect effects. The residual effect showed that 37.9% of variation in aspiration was explained by the selected variables.

INTRODUCTION

Rural youth are a key human resource for agricultural development, and their aspirations strongly influence their engagement in agriculture (Umesh & Tekale, 2019). In India, agriculture remains a key source of income, and youth involvement is vital for sustainability, productivity, and food security. Despite this, rural areas face unemployment and food insecurity. The

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agricultural sector has the potential to address these challenges by generating employment and ensuring stable food production (Bagson et al., 2013). It acts as an important economic sector that contributes to livelihood through the provision of employment, if the right policies are put in place. This explains the relevance of involving young people in agriculture towards sustainable growth of the sector (Man, 2012).

Entrepreneurship enhances productivity, generates employment, and improves the socio-economic status of rural youth (Modak et al., 2018; Kiran et al., 2025). Entrepreneurial spirit among rural youth is determined by their aspirations, motivations, and willingness to involve themselves in agriculture and related activities (Singh et al., 2026). However, youth participation in agriculture is hindered by several barriers, including limited access to technological information, inadequate training, and weak extension services (Shanjeevika et al., 2018). This reduces youths' self-confidence and limits their participation in agriculture. Education has mixed effects it enhances knowledge but also exposes youth to more lucrative non-farm career opportunities (Agwu et al., 2014). Apart from education, social and family influences contribute to youths' aspirations. Social capital that comprises family background and educational institutions largely affects youths' career choices (Byun et al., 2012). On the other hand, experience with family farming, household size and career orientation play an important role in affecting youth interest in agriculture (Kumar et al., 2011; Dhakre, 2014).

Rural youth out-migration is rising as urban lifestyles promise better opportunities (Sumberg et al., 2012). Irregular farm income, limited jobs, and crop losses drive this trend (Sai et al., 2024). Adult-focused initiatives restrict youth access to support, threatening agricultural sustainability despite youths' innovative potential (Rogers, 1995). Youth perceptions of farming such as risk and social status influence their aspirations, while access to information and positive role models encourages their involvement (Anyidoho et al., 2012). The declining number of farmers and youth engagement in farming activities in India further underlines the need for action (Sainath, 2016; Tripathi et al., 2018).

Although many studies address youth participation in agriculture, limited research exists on farm youth aspirations, particularly in tribal and underdeveloped areas. Tribal regions like Rayagada in Odisha face distinct socio-economic challenges such as resource constraints, poor infrastructure, and limited extension exposure that influence youth aspirations. This highlights a clear knowledge gap and the need for location-specific studies. Identifying the determinants of the aspiration of farm youth in such areas will contribute to creating successful extension programmes. It will make it possible to conduct programmes to increase the level of participation and achieve sustainable agricultural growth. Therefore, the present study was undertaken with the objective to assess the level of aspiration of farm youth towards agriculture.

METHODOLOGY

The study used an ex-post facto design, as the variables had already occurred and were beyond the researcher's control. This approach enabled systematic investigation of existing phenomena. The research was conducted in Rayagada district of Odisha during 2023–2024. In this study, "aspiration towards agriculture" was operationally defined as the degree to which farm youth sets his goal in relation to his physical, mental attributes and environmental method suggested by Likert (1932) in developing a summated rating scale was followed in the construction of the aspiration scale. The split-half method, along with the Spearman–Brown prophecy formula, was employed to assess the reliability of the scale, and aspiration was measured using a structured scale developed by Preethi (2015), which consisted of 14 statements for studying aspiration of farm youth towards agriculture, the response was collected on a four-point continuum, like no change, low, medium and high, with assigned score of 0,1,2,3. The minimum and maximum scores one could obtained was 0 and 42, respectively and based on the total cumulated score obtained, the farm youth were classified into three categories: low. medium and high based on the mean and standard deviation.

Rayagada, Odisha was purposively selected for its agrarian economy and large tribal population (>55%) (KVK Rayagada, 2023; Census, 2011). In addition, the district is dominated by subsistence farming methods, traditional agricultural practices, and limited income generation through agriculture, which makes it an ideal setting to explore the aspirations of young people for agriculture. The blocks of Rayagada and Gunupur were purposefully selected owing to the level of agriculture practiced within them and the availability of a considerable number of farm youth practising agriculture. Five villages were purposefully selected from each of the blocks to ensure adequate heterogeneity in the study location in terms of access to extension programs, proximity, and farming practices. Fifteen farm youth were randomly selected from each village, with the probability of selection being equal among all individuals, thereby improving the representativeness of findings. Overall, a sample size of 150 farm youth was selected, with 75 from each block.

Data were analyzed using appropriate statistical tools. Pearson's correlation coefficient was used to examine relationships between independent and dependent variables, regression analysis to assess the influence of each independent variable, and path analysis to identify variables with the strongest direct effects.

RESULTS

The relationship between selected personal, socio-economic, psychological, and communication characteristics of farm youth and their level of aspiration was analyzed to understand the influencing factors. The results of the correlation analysis are presented in Table 1.

Table 1. Relationship of Personal, Socioeconomic, Psychological and Communication Factors with Aspiration of Farm Youth

Variables	Correlation coefficient
Age	0.280**
Farming experience	0.290**
Family income	0.330**
Risk orientation	0.463**
Innovative proneness	0.623**
Farming commitment	0.684**
Economic motivation	0.433**

** significance at 1 % level ($p<0.01$)

Correlation analysis was conducted to examine the nature and magnitude of the relationship between selected independent variables and the dependent variable. The findings revealed that out of fourteen independent variables, six variables exhibited a significant relationship with the dependent variable, while Table 1 clearly indicates that the dependent variable was not influenced uniformly by all characteristics, but rather by selected personal, economic, and psychological factors. In respect of personal characteristics, age had a significant positive correlation (r = 0.280), meaning that greater age implied high involvement. This means that the relatively old farm youth were involved, and this could be attributed to their maturity and responsibility to make decisions. Similarly, farming experience had a significant positive correlation (r = 0.290), thus showing that experience played a major role in their behaviour. The family income had a positive and highly significant correlation (r = 0.330), implying that the respondents whose families had financial stability were actively involved. This could have been because of having resources and economic capability.

Psychological traits had the strongest effect on the behaviour of farm youth. This is clear from the fact that the farming commitment had the greatest positive and significant correlation (r = 0.684), followed by innovative proneness (r = 0.623), risk orientation (r = 0.463) and economic motivation (r=0.433). These findings indicate that respondents who were committed to farming, open to innovation, willing to take risks, and motivated by economic gains demonstrated higher levels of involvement. Multiple regression analysis was carried out to determine the combined effect of selected personal, socio-economic, psychological, and communication variables on the aspiration level of farm youth. The results of the regression analysis are presented in Table 2, which shows the contribution of each independent variable in explaining the variation in aspiration.

The multiple regression analysis was conducted to determine the contribution of certain independent variables towards the aspiration of farm youth. As per the findings presented in Table 2, out of fourteen variables, a few variables had a significant impact on the aspiration of farm youth. Education (X_2) had a significant impact on the aspiration of farm youth, and it was found to be positive (t = 2.333). This implies that higher education levels increase the level of aspiration among farm youth. Innovative proneness (X_9) had a highly significant impact on the level of aspiration, and it was found to be positive (t = 2.684), which implies that high innovative proneness among farm youth is likely to enhance their level of aspiration. Farming commitment (X_{10}) was found to be the most significant variable, with a highly significant positive impact on aspiration, i.e., the more the commitment to farming, the higher the aspiration level. Economic motivation (X_{11}) was also found to have a positive and highly significant impact on aspiration, i.e., the economically motivated youth have higher aspiration levels. Farming experience (X_4) was also found to have a positive contribution to aspiration. From the findings, it can be inferred that the psychological and motivational variables have a more significant contribution to the aspiration of farm youth compared to the other variables, i.e., socio-economic and communication variables.

To further understand the causal relationships among the selected variables influencing the aspiration of farm youth towards agriculture, path coefficient analysis was conducted. The results showing the direct and indirect effects of the variables on aspiration are presented in Table 3.

The path analysis in Table 3 shows how different variables affect farm youth getting involved in agriculture, with some direct impacts and others working through indirect paths. Farming experience stands out the most, with a direct effect of 0.462 and a total of 0.839, so it really pushes participation up a lot, since more time on the farm probably gets people more committed to sticking with it. Age has a high direct impact value of (0.428) and a total effect of (0.620). Older youth are more willing to participate. The ninth variable is innovative proneness with a value of 0.239). Family size has a positive influence, as well as the value of (0.191). Land holding are also valuable direct influences, together with mass media use, which have positive direct value of (0.136) and (0.088), respectively, but also some indirect impacts. While education's direct value is relatively low at (-0.024), its indirect effect is high at (0.484); thus, its total value is (0.460). This indicates that education indirectly impacts the process of participation. A similar pattern appears for Cosmopoliteness (-0.133) and Economic

Table 2. Multiple Regression Analysis of Aspiration of Different Youth Parameters

Factors	Variables	"t" value	Regression coefficient "b" value	standard error (SE)
X_1	Age	2.000*	0.002	0.001
X_2	Education	2.333*	0.007	0.003
X_3	Family size	-1.750 NS	-0.014	0.008
X_4	Farming Experience	1.000 NS	0.003*	0.003
X_5	Land holdings	-1.667 NS	-0.005	0.003
X_6	Family income	-0.472 NS	-0.002	0.004
X_7	Leisure activities	-0.786 NS	-0.011	0.014
X_8	Risk orientation	-0.158 NS	-0.006	0.038
X_9	Innovative proneness	2.684**	0.102**	0.038
X_{10}	Farming commitment	5.667**	0.085**	0.015
X_{11}	Economic motivation	3.068**	0.224**	0.073
X_{12}	Extension contact	-1.000 NS	-0.003	0.003
X_{13}	Mass media use	-1.600 NS	-0.008	0.005
X_{14}	Cosmopoliteness	0.833 NS	0.005	0.006

*P <0.05, *P<0.01, NS- Non Significant, The t- values were computed as the ratio of the regression coefficient (b) to its standard error (SE).

Table 3. Direct and Indirect Effect of Path coefficient of farm youth towards agriculture

Variable	Direct effect	Total indirect effect	Total effect*
X_1	0.428	0.192	0.620
X_2	-0.024	0.484	0.460
X_3	0.191	0.240	0.431
X_4	0.462	0.377	0.839
X_5	0.136	0.154	0.290
X_6	-0.024	0.024	0.000
X_7	-0.068	-0.031	-0.099
X_8	0.031	-0.001	0.030
X_9	0.239	-0.064	0.175
X_{10}	0.137	-0.105	0.032
X_{11}	0.142	0.021	0.163
X_{12}	-0.140	0.138	-0.002
X_{13}	0.088	0.203	0.291
X_{14}	-0.133	0.382	0.249

Where, X_1-Age, X_2- Education, X_3-Family Size, X_4-Farming Experience, X_5-Land Holdings, X_6- Family Income, X_7-Leisure Activities, X_8-Risk Orientation, X_9-Innovative Proneness, X_{10}-Farming commitment, X_{12}-Economic motivation, X_{13}-Mass Media use X_{14}-Cosmopoliteness, *Residual Effect 2 =0.379*

motivation (-0.140), where their indirect values balance the process at a fairly moderate level. Leisure activities hurt participation in farm work, both in terms of the direct impact of (-0.068) and the total effect of (-0.099.) Spending more time on fun stuff might pull youth away from farm work. Family income, risk orientation, and farming commitment don't do much, with tiny total effects like 0.032 for commitment; hence they're not big players here.

The residual effect squared was found to be 0.379, indicating that 37.9 per cent of the variation in farm youth participation towards agriculture was not explained by the variables included in the model. However, 62.1 per cent of the variation was explained by the selected independent variables, suggesting a moderate explanatory power of the model. From the above findings, it can be inferred that the psychological and motivational variables have a more significant contribution to the aspiration of farm youth compared to the other variables, i.e., socio-economic and communication variables.

DISCUSSION

In the current research, it has been seen that there is a positive and significant effect of age and farming experience on the aspirations of youth working on the farms to be engaged in agriculture. Thus, there is evidence that aspirations increase with increasing age and engagement in farming-related tasks. These finding are consistent with the results of Singh and Rao (1996), wherein they observed the presence of a significant correlation between age and aspiration. It has been seen that there is a significant effect of education on aspiration, and this finding is in line with the results obtained by Hadagali (2013). Nevertheless, the minor impact of education on promoting agricultural aspirations is consistent with the observation of Bhanu (2006), according to whom higher education levels encourage rural youth to opt for non-agricultural jobs because of higher incomes and social status. Farming experience was identified as one of the determinants of aspiration, thus confirming the significance of experience-based learning as a major aspect of the formation of positive attitudes toward farming. These results agree with the findings presented by Farouque and Hiroyuki (2007), according to whom farming experience influences the farmer's decision-making skills and perception. With regards to the psychological determinants of aspiration, innovativeness, risk orientation, economic motivation, and farming commitment were found to have strong positive correlations with the variable under study. These results correspond with those obtained by Bhanu (2006) in relation to innovativeness and economic motivation. In turn, Raksha et al. (2012) demonstrated the significance of risk orientation in decision-making that confirms the contribution of this characteristic to agricultural aspiration. Furthermore, economic motivation was found to have both direct and indirect impacts on aspiration, which agrees with Hanchinal (1999) reporting medium to high levels of economic motivation among rural youth.

Path analysis revealed greater insight into how variables impact aspiration. Even though some of the variables failed to show a substantial impact directly, they showed a great contribution indirectly. In addition, economic motivation was important since it indirectly impacted innovativeness, extension contact, and information access. This means that economically motivated youths are more active in looking for information, hence their agricultural aspirations. The indirect contributions made by extension contact and mass media reveal the role of communication sources on youths' aspirations. These findings are supported by Hadagali (2013), who reported that extension participation and mass media utilisation significantly influence youth aspiration. Similarly, cosmopoliteness contributed indirectly by broadening exposure and enabling youth to perceive agriculture from a more modern and entrepreneurial perspective. Path analysis sheds much more light on the nature of the variables' influence on aspiration. Some variables were found to be less influential directly, but they still exhibited indirect significance in shaping aspirations. Particularly, economic motivation was found to play a very important indirect role in influencing innovativeness, extension contact and information exposure. In other words, youth who are economically motivated will be better prepared to look for information and opportunities, which in turn will contribute to greater agricultural aspirations. Extension contact and mass media use had indirect effects on youth aspirations. While socio-economic factors provide context, psychological factors exert greater influence. The study both supports and challenges earlier findings, offering insights for tribal areas like Rayagada. An integrated approach emphasizing psychological empowerment and experiential learning is essential.

CONCLUSION

The aspiration of farm youth towards agriculture is influenced more by psychological attributes and farming experience than by demographic factors. Innovativeness, risk orientation, economic motivation, and farming commitment emerged as key determinants, while extension contact, mass media exposure, and Cosmopoliteness contributed indirectly to shaping positive attitudes. These findings emphasise the need for youth-focused policies that strengthen psychological competencies and motivation towards agriculture. Policymakers should promote programmes that enhance innovation,

risk-taking ability, and access to information. From an extension perspective, organising skill-based training, promoting Agri-entrepreneurship, and improving extension outreach are essential to enhance youth engagement. Facilitating exposure to modern communication channels and progressive farming practices can further strengthen aspiration levels. Overall, a comprehensive approach integrating capacity building, innovation, and effective extension support is crucial for sustaining youth participation in agriculture.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the respondents and their organisations regarding the study during the course of the data collection.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The author declares that they have thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Women's Agency and Family Planning Counselor Roles in Child Nutrition: Semi-Urban Yogyakarta Survey

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HIGHLIGHTS

- Women's household agency predicted child nutrition practices (β = 0.740, p = 0.008).
- Family Planning Counselor roles had a significant positive effect (β = 0.189, p = 0.043).
- Women's agency and counselor roles were positively associated (r = 0.309, p = 0.005).
- Plant protein, dietary diversity, and micronutrient practices remained comparatively weak.

ARTICLE INFO

Keywords: Women's agency, Family planning counselors, Child feeding practices, Stunting-risk households, Extension communication, Structural equation modeling, Semi-urban Indonesia.

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ABSTRACT

Child nutrition in semi-urban settings depends not only on food access but also on household decision-making and community counseling. This study examined the effects of women's household agency and Family Planning Counselor roles on child nutrition practices among stunting-risk households in semi-urban Yogyakarta, Indonesia. A cross-sectional survey was conducted in 2025 with 182 households in Sleman Regency, Bantul Regency, and Yogyakarta City. Data were collected through structured interviews and analyzed using Structural Equation Modeling. Women's household agency had a strong positive effect on child nutrition practices (β = 0.740, p = 0.008), while counselor roles as educators, communicators, and facilitators had a smaller but significant positive effect (β = 0.189, p = 0.043). The two constructs were positively correlated (r = 0.309, p = 0.005), indicating that stronger household agency was associated with stronger counseling support rather than proving a causal interaction. Together, they explained 67.0% of the variance in child nutrition practices. Animal protein intake and energy adequacy were relatively stronger, whereas plant protein intake, dietary diversity, and micronutrient-related practices were weaker. The study concluded that extension-based nutrition support should combine household agency strengthening with practical counseling and facilitation for stunting-risk families.

INTRODUCTION

Child nutrition remains a critical issue in family welfare and human development because inadequate feeding practices during early childhood can affect physical growth, cognitive development, educational achievement, and long-term productivity (Black et al., 2013; Keats et al., 2021). Stunting is particularly important because it reflects chronic nutritional deprivation and may produce long-

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term consequences for children's health, learning capacity, and human capital formation (Rezaeizadeh et al., 2024; Soliman et al., 2021). Therefore, child nutrition should not be understood only as a biomedical issue, but also as a family behavior, caregiving, and development communication issue (Ahmed et al., 2021; Keats et al., 2021).

In Indonesia, stunting has declined but remains a major public concern, with national data reporting a prevalence of 21.5 per cent in 2023 and 19.8 per cent in 2024 (Kemenkes, 2025). Yogyakarta provides an important empirical setting because the province has relatively high human development, yet several districts continue to experience nutrition vulnerability among children and families (BPS Indonesia, 2024; BPS Provinsi D.I. Yogyakarta, 2024). This condition suggests that child nutrition problems in semi-urban settings are not explained only by food availability or service access, but also by gaps in household practice, caregiving routines, and the adoption of recommended feeding behavior (Ahmed et al., 2021; Pienaah et al., 2025). At the household level, women are central actors in childcare, food preparation, hygiene routines, and daily family welfare management (Komakech et al., 2022). Women's household agency is therefore important because nutrition information can influence child feeding only when women have the confidence, authority, and decision-making space to apply it in everyday family life (Komakech et al., 2022; Rezaeizadeh et al., 2024). At the community level, Family Planning Counselors can function as extension actors who support family welfare through education, communication, referral linkage, and facilitation (BKKBN, 2021). This role is consistent with evidence that infant and young child feeding interventions are more effective when nutrition education, interpersonal counseling, community delivery, and practical support are combined rather than delivered as single-message interventions (Ahmed et al., 2021; Keats et al., 2021). Child nutrition counseling has also been associated with higher child dietary diversity, especially when feeding decisions are supported by intra-household cooperation and gender-sensitive family dynamics (Pienaah et al., 2025). Evidence from extension-based interventions further shows that meetings, lectures, discussions, counseling sessions, home visits, audio-visual aids, and mobile-based information can improve rural women's knowledge, attitudes, and practices related to maternal and child health (Singh & Bisht, 2021). Practical household-level interventions, such as nutri-gardens and small-scale vegetable production using grow bags and seeds, have also been shown to improve household food access, nutritional diversity, women's nutritional status, and food security (Kumari et al., 2019; Meenakshi et al., 2019). These findings indicate that nutrition improvement requires not only information delivery, but also practical extension support, women's participation, and household-level facilitation.

This study is informed by Social Cognitive Theory, which views health behavior as the result of interaction between personal agency, environmental support, and behavioral practice (Bandura, 2004). In this framework, women's household agency represents the personal and relational capacity to act within the family, while Family Planning Counselor roles represent the social and communicative support that may strengthen recommended feeding behavior (Bandura, 2004). Although previous studies have examined women's empowerment, maternal education, nutrition counseling, and child dietary diversity, these factors are often analyzed separately rather than as connected household and community-level mechanisms (Komakech et al., 2022; Pienaah et al., 2025; Rezaeizadeh et al., 2024).

METHODOLOGY

This study used an explanatory quantitative design with a cross-sectional household survey to analyze the relationships among women's household agency, Family Planning Counselor roles, and child nutrition practices among stunting-risk households (Creswell & Creswell, 2018). The study was conducted in Sleman Regency, Bantul Regency, and Yogyakarta City, Special Region of Yogyakarta, Indonesia. These locations were selected because they represent semi-urban areas in the Yogyakarta metropolitan region, characterized by urban–rural transition, access to public services and markets, and registered concentrations of stunting-risk households.

The sampling frame was obtained from the official database of stunting-risk households maintained by the National Population and Family Planning Agency. The three study locations were treated as sampling strata, and proportional stratified random sampling was applied according to the distribution of registered stunting-risk households in each district or city. A total of 200 households were initially selected to meet the sample adequacy requirement for Structural Equation Modeling with multiple latent constructs and observed indicators (Hair et al., 2021). After screening incomplete responses and multivariate outliers using Mahalanobis distance, 182 valid cases were retained for analysis.

Data were collected from January to July 2025 through face-to-face interviews using a structured questionnaire in Indonesian. The instrument measured three latent constructs. Women's household agency was measured through the roles of wife, mother, and household manager. Family Planning Counselor roles were measured through educator, communicator, and facilitator functions. Child nutrition practices were measured through animal protein intake, plant protein intake, dietary diversity, energy-related adequacy, and micronutrient-related adequacy. All items used a five-point Likert scale ranging from 1 = never, 2 = rarely, 3 = sometimes, 4 = frequently, to 5 = very frequently. Higher scores indicated stronger household agency, more frequent counselor support, or better child nutrition practices.

Descriptive statistics were used to summarize the study variables. Reliability and convergent validity were assessed using Cronbach's alpha, composite reliability, standardized loading factors, and Average Variance Extracted (Hair et al., 2021). Structural Equation Modeling was conducted using IBM SPSS AMOS [insert version], while descriptive and reliability analyses were conducted using IBM SPSS Statistics [insert version]. Model fit was evaluated using Chi-square probability, Comparative Fit Index, Tucker-Lewis Index, Goodness of Fit Index, Adjusted Goodness of Fit Index, and Root Mean Square Error of Approximation. Procedural and post hoc remedies were applied to reduce common method bias (Podsakoff et al., 2003). Ethical approval was obtained before fieldwork from the Research Ethics Committee of the Academic Hospital of Universitas Gadjah Mada under clearance number [insert

correct clearance number and approval date], and informed consent was obtained from all respondents.

RESULTS

The analysis was based on 182 valid household cases. The achievement score (%) represents the observed score converted into a 0-100 scale by comparing the obtained score with the maximum possible score. The scores were interpreted using five categories: 0-20 = never, >20-40 = rarely, >40-60 = occasionally, >60-80 = frequent, and >80-100 = very frequent. Based on these criteria, the descriptive results showed an uneven pattern across the three study constructs.

Women's household agency was strongest in the roles of wife and mother, both of which were categorized as very frequent, while the household manager role was only categorized as occasional. Family Planning Counselor roles were more visible in educational and communication functions than in facilitation. For child nutrition practices, animal protein intake and energy-related adequacy were more frequently practiced than plant protein intake, dietary diversity, and micronutrient-related adequacy. This pattern indicates that family care and counselor support were present, but their implementation was not equally strong across all dimensions. The descriptive profile of the study variables is presented in Table 1.

The descriptive pattern suggests that women's household agency was more strongly expressed through caregiving and relational roles than through broader household management activities. Similarly, counselor support appeared stronger in information delivery than in practical facilitation, indicating that families may receive nutrition messages more often than follow-up assistance, referral linkage, or problem-solving support. In nutrition practices, the stronger performance of animal protein intake and energy adequacy indicates that households were more consistent in familiar and routine feeding practices. However, the weaker scores for plant protein intake, dietary diversity, and micronutrient-related adequacy suggest partial adoption of recommended child feeding practices. These descriptive findings provide the basis for examining whether household agency and counselor roles explain child nutrition practices in the structural model.

Based on this descriptive pattern, the final structural model was estimated to test the relationships among women's household agency, Family Planning Counselor roles, and child nutrition practices, as presented in Figure 1.

The measurement model was evaluated before interpreting the structural paths. All constructs met the recommended reliability and convergent validity criteria, with composite reliability values above 0.70 and Average Variance Extracted values above 0.50. The standardized loading ranges also showed that the observed dimensions were sufficiently related to their respective latent constructs. Women's household agency showed adequate reliability, while Family Planning Counselor roles and child nutrition practices showed stronger internal consistency. The measurement quality statistics are summarized in Table 2.

The final structural model showed acceptable fit with the observed data. The model achieved Chi-square = 40.888, degrees of freedom = 33, Chi-square/degrees of freedom ratio = 1.239, p = 0.163, Root Mean Square Error of Approximation (RMSEA) = 0.036, Comparative Fit Index (CFI) = 0.994, Tucker-Lewis Index (TLI) = 0.989, Goodness of Fit Index (GFI) = 0.961, and Adjusted Goodness of Fit Index (AGFI) = 0.923. The non-significant Chi-square probability, low RMSEA, and high incremental fit indices indicate that the hypothesized model was suitable for interpreting the relationships among the latent constructs. The structural estimates are presented in Table 3.

Table 1. Descriptive summary and achievement categories of study variables

Variable / Dimension	Achievement (%)	Category
Women's household agency: Role as wife	84	Very frequent
Women's household agency: Role as mother	83	Very frequent
Women's household agency: Role as household manager	56	Occasionally
Family Planning Counselor roles: Educator	66	Frequent
Family Planning Counselor roles: Communicator	65	Frequent
Family Planning Counselor roles: Facilitator	56	Occasionally
Child nutrition practices: Animal protein intake	65	Frequent
Child nutrition practices: Plant protein intake	51	Occasionally
Child nutrition practices: Dietary diversity	59	Occasionally
Child nutrition practices: Energy-related adequacy	67	Frequent
Child nutrition practices: Micronutrient-related adequacy	57	Occasionally

Note: Achievement (%) was calculated by converting the obtained score to the maximum possible score on a 0-100 scale. Categories were defined as 0-20 = never, >20-40 = rarely, >40-60 = occasionally, >60-80 = frequent, and >80-100 = very frequent.

Table 2. Measurement quality of latent constructs

Latent construct	Standardized loading range	AVE	Composite reliability	Cronbach's alpha
Women's household agency	0.57-0.79	0.612	0.822	0.703
Family Planning Counselor roles	0.87-0.95	0.836	0.938	0.930
Child nutrition practices	0.70-0.83	0.610	0.970	0.871

Note: AVE = Average Variance Extracted. The standardized loading range refers to the range of factor loadings for observed dimensions in the measurement model.

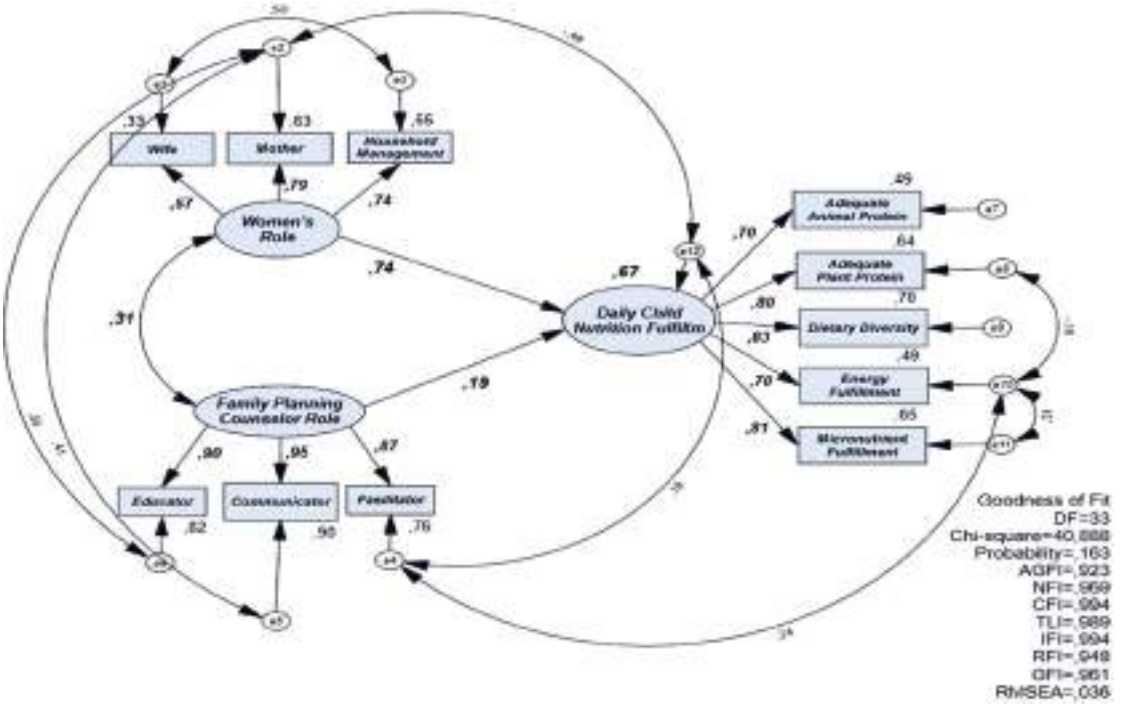


Figure 1. Final structural model with standardized estimates

Note: The model fit was Chi-square = 40.888, degrees of freedom = 33, Chi-square/degrees of freedom ratio = 1.239, p = 0.163, Root Mean Square Error of Approximation = 0.036, Comparative Fit Index = 0.994, Tucker-Lewis Index = 0.989, Goodness of Fit Index = 0.961, and Adjusted Goodness of Fit Index = 0.923.

Table 3. Structural relationships among study constructs

Relationship	Statistic	Estimate	p-value	Decision / interpretation
Women's household agency -> Child nutrition practices	β	0.740	0.008	Accepted; strong positive effect
Family Planning Counselor roles -> Child nutrition practices	β	0.189	0.043	Accepted; smaller positive effect
Women's household agency <-> Family Planning Counselor roles	r	0.309	0.005	Accepted; positive association
Explained variance in child nutrition practices	R^2	0.670	—	Large explanatory power

Note: β = standardized path coefficient; r = correlation coefficient; R^2 = coefficient of determination.

As presented in Table 3, women's household agency had a strong positive effect on child nutrition practices (β = 0.740, p = 0.008). This means that households with stronger women's agency were more likely to demonstrate better routine child feeding practices. Family Planning Counselor roles also had a positive and significant effect on child nutrition practices (β = 0.189, p = 0.043), but the effect was substantially smaller than that of women's household agency. Thus, counselor support contributed to child nutrition practices as an external support factor, while women's household agency remained the dominant explanatory factor.

The positive association between women's household agency and Family Planning Counselor roles was also significant (r = 0.309, p = 0.005), indicating that stronger household agency was associated with stronger counseling support. However, because the study used a cross-sectional design, this association should be interpreted as a statistical relationship rather than evidence of causal complementarity. Together, women's household agency and Family Planning Counselor roles explained 67.0 per cent of the variance in child nutrition practices (R^2 = 0.670). This large explained variance indicates that child nutrition practices in the study area were shaped mainly by internal household capacity and, to a lesser extent, by external counseling support.

DISCUSSION

The findings show that child nutrition practices among stunting-risk households in semi-urban Yogyakarta were explained mainly by women's household agency, while Family Planning Counselor roles provided a smaller but significant contribution. The standardized effect of women's household agency (β = 0.740) was much larger than that of Family Planning Counselor roles (β = 0.189), indicating that daily feeding practices were more strongly shaped by internal household capacity than by external counseling support. This pattern is consistent with evidence that women's empowerment, decision-making authority, and control over household resources are associated with child growth and dietary diversity (Komakech et al., 2022; Rezaeizadeh et al., 2024). In this study, women's roles as wife and mother were stronger than their household management role, suggesting that caregiving and relational agency were more established than broader managerial control over family resources.

The significant but modest effect of Family Planning Counselor roles should be interpreted cautiously. Counselors contributed to child nutrition practices, but their influence was not as strong as women's household agency. This may be explained by the descriptive findings showing that educator and communicator roles were more frequent than facilitation. In practical terms, counselors may have been more active in delivering nutrition messages than in providing follow-up assistance, referral linkage, food planning support, or problem-solving guidance. This interpretation is consistent with evidence that nutrition counseling and community-based behavior change interventions are more effective when repeated interpersonal communication is combined with practical support and household-level decision-making (Ahmed et al., 2021; Keats et al., 2021; Pienaah et al., 2025). Extension education evidence further shows that maternal and child health interventions using home visits, focus group discussions, counseling sessions, lectures, brainstorming sessions, group meetings, audio-visual aids, and mobile-based information can improve rural women's knowledge, attitudes, and practices related to maternal and child health (Singh & Bisht, 2021). The weaker scores for dietary diversity and micronutrient-related practices in the present study also support the need for practical household-level facilitation, because nutri-garden interventions can improve household access to vegetables, food security, nutritional diversity, and the availability of macro- and micronutrients through the provision of bio-fortified vegetable seeds and saplings (Kumari et al., 2019). Similarly, small-scale organic farming support through grow bags and vegetable seeds can help improve women's nutritional status, income, and waste disposal practices (Meenakshi et al., 2019). Therefore, Family Planning Counselor roles should be strengthened not only as educators and communicators, but also as facilitators who provide practical guidance, family engagement, referral linkage, food planning support, and follow-up assistance.

The descriptive findings also show that child nutrition practices were not equally adopted across all dimensions. Animal protein intake and energy-related adequacy were stronger, while plant protein intake, dietary diversity, and micronutrient-related adequacy remained weaker. This pattern indicates partial adoption of recommended feeding practices rather than complete behavioral change. It also suggests that households may be more consistent in familiar and routine feeding behaviors, but less consistent in practices requiring dietary planning, food variation, and sustained attention to micronutrient quality. This finding is relevant to nutrition-sensitive extension because improving child feeding requires not only awareness, but also repeated learning, family negotiation, and practical support for daily food choices (Ahmed et al., 2021; Keats et al., 2021; Pienaah et al., 2025).

The positive association between women's household agency and Family Planning Counselor roles ($r = 0.309$) indicates that the two mechanisms were related, but it should not be interpreted as causal complementarity. Because the study used a cross-sectional design, the relationship only shows that households with stronger agency tended to report stronger counselor support. One possible interpretation is that women with stronger agency may be more able to use counseling information, while counselors may also interact more effectively with households that are more responsive to guidance. However, longitudinal or intervention-based research is needed to confirm whether counseling strengthens agency or whether agency improves the uptake of counseling.

Overall, the study contributes to extension education by showing that child nutrition practices are behavioral outcomes shaped by both household capacity and community-based counseling. The large explained variance of child nutrition practices ($R^2 = 0.670$) indicates that the model captured important determinants, but other factors such as household income, food prices, family support, cultural preferences, and local food availability may also influence feeding behavior. For practice, stunting prevention in semi-urban families should prioritize women's agency strengthening, family engagement, repeated nutrition counseling, referral facilitation, and food demonstration, especially for dietary diversity, plant protein, and micronutrient-rich foods.

CONCLUSION

The child nutrition practices among stunting-risk households in semi-urban Yogyakarta were shaped more strongly by women's household agency than by Family Planning Counselor roles. Women's agency was the dominant factor in routine child feeding practices, while counselor support provided a smaller but significant contribution through education, communication, and facilitation. The nutrition improvement in semi-urban families cannot rely only on information delivery. It requires women's decision-making capacity, practical household guidance, and sustained community-based support. The extension strategies should prioritize household-level behavior change. Family Planning Counselors should strengthen follow-up counseling, referral linkage, food demonstration, and family-based problem solving rather than focusing only on nutrition messages. Particular attention should be given to the weakest behavioral areas, namely plant protein intake, dietary diversity, and micronutrient-related practices. Programs should combine women's agency strengthening, husband and family engagement, repeated counseling, and practical feeding guidance for stunting-risk households. These targeted strategies may help translate nutrition knowledge into more consistent daily child-feeding practices.

DECLARATIONS

Research ethics statement: Ethical approval for this study was granted by the Research Ethics Committee of the Academic Hospital of Universitas Gadjah Mada (RSA UGM) under Ethical Clearance Number 030/RSA/KEP/EC/2026. The study was conducted in accordance with the principles established by the National Research Ethics Committee and the Guidelines and Standards for Research Ethics and National Health Development issued by the Ministry of Health of the Republic of Indonesia. Informed consent was obtained from all participants prior to data collection.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors further declare that they carefully reviewed, revised, and finalized the manuscript and take full responsibility for the content of this publication.

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Research Article

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Knowledge and Adoption Level of Improved Sorghum Practices in Bundelkhand Region of Uttar Pradesh

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HIGHLIGHT

- Significant knowledge–adoption gap existed in crop protection and seed treatment adoption rates.
- Education, income, landholding, and attitude significantly influenced adoption.
- Knowledge and attitude emerged as strongest predictors of adoption.
- Affordability of key input and climatic constraints driving the knowledge–adoption gap in sorghum cultivation.

ARTICLE INFO

Keywords: Knowledge, Adoption, Sorghum, Technology, Bundelkhand, Uttar Pradesh.

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ABSTRACT

Productivity of sorghum in Bundelkhand remained constraints due to lower adoption of recommended practices. The data were collected for this study during February to April 2024 to assess the knowledge and adoption levels of farmers towards improved sorghum production technologies and to identify their determinants. An ex-post facto research design was followed in two purposively selected districts of Uttar Pradesh. A total of 200 sorghum growers were selected through multistage sampling, and data were collected using a semi structured and pre-tested interview schedule. Descriptive statistics, chi-square test, and regression analysis were used for data analysis. The results revealed that seed rate and sowing time recorded the highest knowledge and adoption scores, whereas crop protection and seed treatment showed the lowest adoption levels. A majority of respondents possessed medium knowledge, but overall adoption still low, indicating a clear knowledge adoption gap. Education, landholding, annual income, attitude, and knowledge score significantly influenced adoption behavior. The study concluded that socio-economic resources and psychological factors played a decisive role in enhancing adoption of improved sorghum technologies. The study revealed a significant knowledge–adoption gap, with input constraints and climatic factors emerging as the major barriers to the adoption of improved sorghum production practices.

INTRODUCTION

Millets have recently attracted significant attention and respect due to their richness in nutritional composition. It is often regarded as a “poor man’s food”, but it is now acknowledged as a superfood with enormous health benefits. The Indian government recognized millets as Nutri-Cereals in April 2018 to promote their production

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and consumption, generating demand both domestically and internationally and giving people access to wholesome food (Yadav et al., 2023). The United Nation also declared 2023 as the International Year of Millets (IYoM-2023) on the proposal of the Government of India (Harish et al., 2024). Among millets, Sorghum is the most commonly cultivated millet crop, with 39.62 million hectares and 58.92 million tons of production globally. Sorghum assumes a crucial role as a cash crop, serving as a vital source of income as well as nutrition for farmers (Rao et al., 2014; Amrutha et al., 2024). Despite India being the fourth-ranking producer (4.4 million tonnes) of sorghum globally in 2023-24 (ANGRAU, 2023–24), it faces challenges of low productivity (Sandeep et al., 2018). According to the Government of India (2022–23) Department of Agriculture and Farmers Welfare, Directorate of Economics and Statistics and Ministry of Agriculture and Farmers Welfare, the Bundelkhand region records approximately 65,461 hectares under sorghum cultivation with a total production of about 105,235 tonnes, resulting in an average productivity of 1.61 tonnes per hectare (Sah et al., 2021). Modern agricultural technologies provide an achievable way to increase production, strengthen resilience, and eventually improve household food security (Vattekkad et al., 2025). These technologies include improved seed varieties (HYVs) and mechanization to climate-smart agriculture (CSA) practices and digital tools (Senyolo et al., 2021). Bundelkhand region of Uttar Pradesh is basically depend upon agriculture yet it faces significant challenges regarding natural calamities and low level of urbanization. Sustainable livelihood is also difficult due to combination of irregular rainfall, low crop yield and poor economic returns. Under the Bundelkhand condition, sorghum is considered a climate-resilient crop due to its drought tolerance and adaptability under moisture stress, making it an important for region. Adoption of improved sorghum cultivation practices increases the productivity and facilitates the growth of non-farm and agro-processing businesses, and accelerates the shift from low-productivity subsistence farming to a high-productivity agro-industrial economy (Just & Zilberman, 1988). Adoption of many of the improved technologies is low, which creates a larger problem of suboptimal production and necessitates greater regulatory action (Jat et al., 2022; Singh et al. 2023). Most studies emphasize that access to information and asset holdings (financial, natural, human, and social) (Aryal et al., 2019; Deressa et al., 2009; Khanal et al., 2018; Singh, 2015) play a crucial role in the adoption of these techniques (Veettil et al., 2021). Existing studies indicate a significant decline in sorghum area and production in the Bundelkhand region, with nearly 59% reduction in area during 2000–2020, despite its suitability for drought-prone conditions. Productivity levels also remain relatively low, suggesting underutilization of improved technologies, while a negative relationship between irrigation expansion and millet cultivation reflects a shift away from sorghum (Sah et al., 2021). Therefore, a clear research gap exists in understanding the knowledge and adoption level of improved sorghum practices among farmers in Bundelkhand, which is essential to bridge the gap between technology availability and its field-level utilization.

METHODOLOGY

The study was conducted in the Bundelkhand region of Uttar Pradesh, India. It consisted of seven districts namely Banda, Hamirpur, Chitrakoot, Mahoba, Jhansi, Lalitpur and Jalaun. Out of these districts Banda and Chitrakoot districts were selected purposively for the study because both the districts were leading in area and production in Bundelkhand. Two blocks from each district Baberu and Tindwari from Banda, and Karwi and Mau from Chitrakoot were purposively selected for the study due to having comparatively higher area and productivity of sorghum. Data was gathered through Personal interview with the help of a standardized and pre-tested survey questionnaire. Key socioeconomic factors (such as gender, age, family size, education level, consumption expenditures, membership in farmers' organizations, extension offices, institutional and other pertinent factors and distance of a residence from input and output markets) were gathered during the in-person interviews regarding the sorghum varieties grown. From each of the selected four blocks, a list of sorghum-growing villages was prepared in consultation with officials from the Department of Agriculture. Villages were ranked based on the area under sorghum cultivation. Subsequently, five villages from each block (total 20 villages) were selected purposively. From each selected village a list of sorghum-growing farmers was compiled with the help of the respective *Gram Pradhans* and local leaders. From each village, 10 farmers were selected using a simple random sampling technique, employing a random number table to ensure unbiased representation. Thus, a total of 200 respondents (20 villages × 10 farmers). This stratified yet randomised approach ensured both relevance and statistical rigour in data collection. The data was collected from February to April, 2024. An ex-Post Facto and descriptive research design was used for the study as the events had already occurred. A schedule was created to assess farmers' familiarity with specific technologies that were recommended for the sorghum crop. To measure the extent of Knowledge and Adoption a knowledge and adoption test was developed. The response of respondents regarding knowledge was categorised into a three-point continuum (fully knowledge, partial knowledge and poor knowledge) and adoption using (complete, partial and no adoption). The constraints faced by farmers were identified and analyzed using the Garrett ranking technique, wherein respondents ranked the constraints based on their severity. The obtained ranks were converted into percent positions and corresponding Garrett scores, and the mean scores were calculated to determine the final ranking of constraints. Each response was tabulated on MS Excel. Frequency, percentage, class interval method and chi-square test were used to analyse the data with the help of MS Excel and Statistical Package for Social Science (SPSS). To find major determinats affecting the Knowledge and Adoption of the respondents multiple regression is used. As different variables are measured on different level of measurement Z transformation is used to standardize all the variables.

RESULTS

Practice-wise Information on the distribution of respondents regarding the extent of adoption and knowledge of recommended sorghum production technologies (Table 1) shows that there was variation across sorghum production technologies in terms of knowledge and adoption based on Mean Percent Scores (MPS) and rank order. With the highest MPS of 86.50, the seed rate achieved the top spot in terms of knowledge. Sowing time (MPS = 78.17,

Table 1. Knowledge and adoption of sorghum practices

S.No.	Production Technology	Knowledge		Adoption	
		MPS	Rank	MPS	Rank
1	Land Preparation	72.72	III	73.83	III
2	Sowing Time	78.17	II	78.83	I
3	Seed Rate	86.50	I	78.17	II
4	Spacing	59.83		65.50	V
5	Seed Treatment	61.33	VII	49.83	VI
6	Fertilizer Application	71.83	IV	70.33	IV
7	Weed Control	65.54	V	60.67	V
8	Crop Protection	64.83	VI	45.67	VII

Rank II) and land preparation (MPS = 72.72, Rank III) came next. Fertilizer application occupied the fourth rank with an MPS of 71.83, while weed control (MPS = 65.54) and crop protection (MPS = 64.83) were placed at fifth and sixth ranks, respectively. Comparatively lower knowledge was recorded for seed treatment (MPS = 61.33, Rank VII) and spacing (MPS = 59.83, Rank VIII). A similar ranking pattern was also observed for adoption. Sowing time ranked first in adoption with the highest MPS of 78.83, followed closely by seed rate (MPS = 78.17, Rank II) and land preparation (MPS = 73.83, Rank III). Fertilizer application stood at the fourth position with an MPS of 70.33. Practices such as spacing (MPS = 65.50, Rank V) and weed control (MPS = 60.67, Rank VI) occupied middle ranks. The lowest adoption was observed for seed treatment (MPS = 49.83, Rank VII) and crop protection (MPS = 45.67, Rank VIII).

Results of chi-square and multiple regression analysis (Table 2) revealed the association and contribution of selected independent to dependent variables (knowledge level of sorghum growers). The chi-square analysis indicated that education (χ^2 = 18.103), land holding (χ^2 = 14.489), annual income (χ^2 = 16.968), and attitude (χ^2 = 118.321) had a statistically significant association with the knowledge level of respondents. Among these, the association of annual income and attitude was found to be highly significant. In contrast, variables such as age, occupation, social participation, decision-making ability, scientific orientation, risk preference, management orientation, and sources of information credibility did not show a significant association with knowledge level. These conclusions were further supported by the regression analysis, which identified important knowledge determinants. Education was found to be a substantial and positive predictor of knowledge level (β = 0.42, t = 3.82, p < 0.01), suggesting that farmers' understanding of suggested sorghum production technology was greatly improved by higher educational attainment. Additionally, land holding had a substantial positive influence (β = 1.87, t = 3.46, p < 0.01), indicating that farmers with bigger landholdings were more knowledgeable. Knowledge was positively and significantly impacted by annual income (β = 0.09, t = 2.98, p < 0.01), indicating the importance of economic strength in gaining access to inputs and information. Additionally, the knowledge level of farmers was found to be strongly influenced by social participation (β = 1.26, t = 2.63, p < 0.01) and the frequency of using information sources (β = 0.31, t = 3.10, p < 0.01). Among the variables, attitude was found to be the most significant driver (β = 0.58, t = 8.29, p < 0.01), indicating that farmers' knowledge is greatly enhanced by having a positive attitude toward sorghum farming. On the other hand, age had a negative but non-significant impact on knowledge level, suggesting that respondents' age had no effect on their acquisition of information.

The results of chi-square analysis (Table 3) indicated that several independent variables were significantly associated with the adoption level of sorghum production technologies. Education (χ^2 = 23.765), land holding (χ^2 = 16.756), annual income (χ^2 = 18.005), social participation (χ^2 = 15.050), decision-making ability (χ^2 = 13.565), risk preference (χ^2 = 25.819), management orientation (χ^2

Table 2. Association and determinants of the knowledge level

S.No.	Independent Variable	Chi-square (χ^2)	p-value (χ^2)	β coefficient	Std. Error	t-value	p-value (Regression)
1	Age	3.457	0.484	–0.03	0.02	–1.45	0.149
2	Education	18.103	0.053	0.42	0.11	3.82	0.000**
3	Land holding	14.489	0.025*	1.87	0.54	3.46	0.001**
4	Annual Income	16.968	0.002**	0.09	0.03	2.98	0.003**
5	Occupation	1.581	0.954	—	—	—	—
6	Social Participation	2.876	0.824	1.26	0.48	2.63	0.009**
7	Scientific Orientation	8.124	0.087	—	—	—	—
8	Decision Making	9.232	0.056	—	—	—	—
9	Risk Preference	7.653	0.105	—	—	—	—
10	Management Orientation	1.468	0.832	—	—	—	—
11	Source of Information (Frequency)	5.390	0.250	0.31	0.10	3.10	0.002**
12	Source of Information (Credibility)	8.743	0.068	—	—	—	—
13	Attitude	118.321	0.001**	0.58	0.07	8.29	0.000**

Table 3. Association and determinants of the adoption level

S.No.	Independent Variable	Chi-square (χ^2)	p-value (χ^2)	β coefficient	Std. Error	t-value	p-value (Regression)
1	Age	7.317	0.120	—	—	—	—
2	Education	23.765	0.008**	0.36	0.10	3.60	0.000**
3	Land holding	16.756	0.010**	1.45	0.49	2.96	0.003**
4	Annual Income	18.005	0.001**	0.12	0.04	3.00	0.003**
5	Occupation	9.829	0.132	—	—	—	—
6	Social Participation	15.050	0.020*	1.09	0.45	2.42	0.016*
7	Scientific Orientation	4.436	0.350	—	—	—	—
8	Decision Making Ability	13.565	0.009**	—	—	—	—
9	Risk Preference	25.819	0.001**	0.51	0.13	3.92	0.000**
10	Management Orientation	19.011	0.001**	0.47	0.14	3.36	0.001**
11	Source of Information (Frequency)	25.692	0.001**	0.38	0.11	3.45	0.001**
12	Source of Information (Credibility)	29.316	0.001**	—	—	—	—
13	Attitude	19.602	0.001**	0.41	0.08	5.12	0.000**
14	Knowledge Score	14.283	0.006**	0.62	0.09	6.89	0.000**

= 19.011), source of information (frequency and credibility), attitude (χ^2 = 19.602), and knowledge score (χ^2 = 14.283) showed statistically significant associations with adoption level. whereas age, occupation, and scientific orientation show a non-significant association with adoption. The regression table also reveals that education had a significant and positive effect on adoption (β = 0.36, t = 3.60, $p < 0.01$), suggesting that educated farmers are more likely to accept recommended methods. The significance of resource availability in adoption behaviour can be seen by the significant predictors like land holding (β = 1.45, t = 2.96, $p < 0.01$) and annual income (β = 0.12, t = 3.00, $p < 0.01$). A positive and significant relationship was found between social activity and exposure to innovations (β = 1.09, t = 2.42, $p < 0.05$). Adoption behaviour is also significantly influenced by psychological and communication-related factors. Adoption was significantly influenced by risk preference (β = 0.51, t = 3.92, $p < 0.01$) and management orientation (β = 0.47, t = 3.36, $p < 0.01$), suggesting that farmers who were ready to take risks and had superior managerial skills were more likely to adopt improved technology. Adoption was also strongly influenced by the frequency of using information sources (β = 0.38, t = 3.45, $p < 0.01$). Among all variables, attitude (β = 0.41, t = 5.12, $p < 0.01$) and knowledge score (β = 0.62, t = 6.89, $p < 0.01$) show the strongest determinants of adoption, indicating that farmers with better knowledge and a favorable attitude towards sorghum production were significantly more likely to adopt recommended practices.

Among the input and resource constraints regarding adoption of improved package of practices (Table 4), high cost of fertilizers and pesticides (mean score 75.20) was the most severe constraint, followed by the non-availability of quality seeds (73.80) and limited access to seed treatment chemicals (71.50). indicating that farmers are significantly affected by both the affordability and availability of inputs, which directly affect the adoption of improved practices such as seed treatment and crop protection. Environmental and climatic constraints like erratic and inadequate rainfall (72.60) was ranked first, followed by moisture stress during crop growth (70.10) and poor soil fertility (67.95). The findings reflect the drought-prone nature of the Bundelkhand region, where uncertain rainfall and soil limitations discourage farmers from investing in input-intensive technologies. Whereas knowledge, skill and extension constraints, such as lack of practical training on seed treatment (68.90) and inadequate field demonstrations (66.75) were the major constraints. Suggesting that although farmers possess significant level of awareness, the absence of hands-on training and effective extension support limit the actual adoption of recommended practices. Lastly in socio-economic and institutional constraints, small and fragmented landholdings (63.40) ranked first, followed by low income and risk-bearing capacity (61.85) and labour shortage

Table 4. Garrett Ranking of Constraints within Each Category

S. No.	Constraints	Mean Score	Rank
Input and Resource Constraints			
1	High cost of fertilizers and pesticides	75.20	I
2	Non-availability of quality seeds	73.80	II
3	Limited access to seed treatment chemicals	71.50	III
4	Lack of farm machinery for proper spacing	69.90	IV
5	Lack of timely credit facilities	67.85	V
Environmental and Climatic Constraints			
1	Erratic and inadequate rainfall	72.60	I
2	Moisture stress during crop growth	70.10	II
3	Poor soil fertility	67.95	III
4	Lack of irrigation facilities	65.40	IV
5	Increased pest incidence due to climatic stress	63.75	V
Knowledge–Skill and Extension Constraints			
1	Lack of practical training on seed treatment	68.90	I
2	Inadequate field demonstrations	66.75	II
3	Poor contact with extension personnel	64.10	III
4	Difficulty in understanding technical practices	62.85	IV
5	Limited awareness of pest and weed management	60.15	V
Socio-economic and Institutional Constraints			
1	Small and fragmented landholdings	63.40	I
2	Low income and risk-bearing capacity	61.85	II
3	Labour shortage due to migration	60.20	III
4	Poor market support and price fluctuation	58.75	IV
5	Limited government focus on sorghum crop	56.80	V

due to migration (60.20). These factors reduce farmers' ability and willingness to adopt improved technologies, particularly those requiring additional investment and labour.

DISCUSSION

The findings show differences between practices, which shows major insights into the pattern of farmers' awareness and adoption of suggested sorghum production technology. Due to its simplicity, widespread familiarity, and frequent reinforcement through traditional farming experience and extension advisory, basic agronomic practices including seed rate, sowing timing, and soil preparation, have a comparatively greater level of knowledge and adoption. These practices have higher Mean Percent Scores (MPS) and rankings in both knowledge and adoption because they are less input-intensive, carry less risk, and have a direct impact on the growth of crops. These finding are consistent with Bhagat et al. (2002) and Kumar et al. (2025), who reported that fundamental practices like sowing time are more readily adopted due to minimal financial risk.

In contrast, crop protection, weed management, seed treatment, and spacing related practices revealed relatively low levels awareness and high adoption gap similar with Gupta et al. (2021). The low MPS and scores for crop protection and seed treatment could be related to their perceived higher cost-benefit uncertainty, lack of practical demonstrations, restricted availability to high-quality inputs, and technical complexity. According to Kumar et al. (2020), sorghum growers have a large technology gap, particularly in the areas of disease management and insect-pest control. Particularly in situations when resources are limited, farmers frequently view these measures as discretionary rather than necessary. The prevalence of low adoption of crop protection techniques also points to a lack of faith in chemical or integrated management techniques as well as insufficient pest and disease detection abilities. This pattern is further supported by the respondents' overall distribution across adoption and knowledge categories. More than half of the respondents show low adoption levels, though most farmers were categorized as having a medium understanding. This demonstrates clearly the existence of a knowledge-adoption gap, where awareness does not always transfer into actual application. These gaps are frequently seen in agricultural extension research and are frequently impacted by financial constraints, risk aversion, delayed inputs, and inadequate field-level assistance. These findings are also in line with the findings of Nain and Bhagat (2005), Kardak et al. (2006), Nain and Chandel (2013), Patil et al. (2017), Patel et al. (2024), Maurya et al. (2024).

These findings are strongly supported empirically by the association and regression analysis. Adoption was further impacted by risk preference, management orientation. Knowledge score, whereas land holding, education, social participation, annual income, source of information utilization, and attitude were revealed as major factors influencing knowledge. The significant and positive impact of education implies that farmers with higher levels of education are more capable of understanding technical advice and weighing its advantages. In the same manner, farmers are better able to experiment with and implement better techniques when they have larger landholdings and higher income levels. The education, income, and landholding significantly influenced adoption behaviour among farmers (Raina et al., 2014; Kumar et al., 2019; Jat et al. (2022). Attitude was found to be the most significant factor influencing adoption and knowledge, highlighting the psychological aspect of technology adoption. A positive perspective on sorghum farming encourages farmers to learn more and implement suggested methods. Although knowledge is not adequate on its own, it is a prerequisite for adoption, as seen by the knowledge score's substantial impact on adoption. Diffusion theory (Rogers, 2003), which emphasizes that awareness and persuasion come before decision-making and execution, is consistent with this conclusion.

The results also indicate that input and resource constraints, particularly high input costs and non-availability of quality inputs, are the major barriers in adoption of recommended sorghum cultivation practices. Environmental factors such as erratic rainfall and moisture stress further discourage farmers from adopting improved practices. In addition, lack of practical training and weak extension support limit the effective implementation of technical recommendations. Socio-economic issues like small and fragmented landholdings and low risk-bearing capacity also contribute to the gap between knowledge and adoption.

CONCLUSION

The study concluded that farmers have moderate to high knowledge of sorghum production technologies in Bundelkhand, however, the adoption level remains comparatively low and strongly influenced by socio-economic and psychological factors. Basic agronomic practices are widely adopted, whereas technically complex and input-intensive practices remain faces low adoption. A significant knowledge–adoption gap exists, indicating that awareness alone does not ensure implementation. Education, income, landholding, and particularly farmers' attitude and knowledge level significantly play important role in shaping adoption behavior. This gap is also attributed to input constraints, climatic uncertainties, limited extension support, and socio-economic limitations. These findings confirm that technology dissemination is not only to transfer information but also strengthening resource access, risk management capacity, and positive behavioral orientation. Therefore, improving input accessibility, strengthening field-level training and demonstrations, and promoting climate-resilient practices are essential to enhance the adoption of sorghum technologies in the Bundelkhand region.

DECLARATIONS

Ethical statement: The study was conducted in accordance with ethical research standards. Participation was voluntary, and informed consent was obtained from all respondents. The confidentiality and anonymity of participants were strictly maintained throughout the research process.

Conflict of interest: The authors declare that there are no conflicts of interest regarding the publication of this paper. The author declares that they have thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Article

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Agricultural Extension, Farmer Motivation, and Maize Food Security in Indonesia-Timor Leste Borderlands

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HIGHLIGHTS

- Agricultural extension was positively and significantly associated with maize-based household food security in semi-arid borderland households.
- Farmer motivation showed a stronger standardized association with food security than agricultural extension in the final structural model.
- Agricultural extension and farmer motivation jointly explained 55.0% of the variance in household food security.
- The CFA results supported convergent validity, construct reliability, and discriminant validity for all latent constructs.

ARTICLE INFO

Keywords: Extension services, Smallholder motivation, Household food security, Maize farming, Borderland agriculture, Semi-arid systems, Covariance-based SEMm East Nusa Tenggara.

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ABSTRACT

Household food security in semi-arid borderland areas remains vulnerable to drought, limited market access, and weak livelihood assets. Although agricultural extension and farmer motivation have been studied in smallholder contexts, their joint role in explaining maize-based household food security in semi-arid borderland agriculture remains under examined. Drawing on an ERG-based motivation framework, this study tested whether agricultural extension and farmer motivation are positively associated with household food security. A cross-sectional survey of 244 maize-farming households was conducted in the Indonesia–Timor Leste borderlands of East Nusa Tenggara from February to August 2025. Data were collected using a structured questionnaire administered through face-to-face interviews and analyzed using covariance-based structural equation modeling. The final model showed acceptable fit (GFI = 0.997; AGFI = 0.927; CFI = 0.999; TLI = 0.992; RMSEA = 0.050) and explained 55.0% of the variance in household food security. The findings show that agricultural extension and farmer motivation were both positively and significantly associated with household food security, indicating their complementary roles in strengthening maize-based household food security.

INTRODUCTION

Food security is commonly understood through four dimensions: availability, accessibility, utilization, and stability (FAO, 2008). In drylands, these dimensions remain vulnerable because household food systems are shaped by climate variability, land degradation, market instability, limited infrastructure, and restricted access to public services. The State of Food Security and Nutrition

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in the World 2025 emphasizes that high food-price inflation weakens purchasing power and limits access to healthy diets, especially among low-income populations (FAO et al., 2025). Indonesia is also classified as having a moderate level of hunger in the 2025 Global Hunger Index (Global Hunger Index, 2025). However, global and national indicators may conceal regional inequalities because semi-arid borderlands face constraints that differ from irrigated and commercially integrated zones. East Nusa Tenggara is one of Indonesia's vulnerable dryland regions, where maize is not only a crop but also a staple food, household reserve, and subsistence asset. Therefore, national maize production gains do not automatically ensure household-level food security in borderland communities (Silaen et al., 2023; BPS-Statistics Indonesia, 2025).

Agricultural extension provides an institutional mechanism for connecting scientific knowledge, experiential learning, and collective action. In this study, extension is understood not merely as technical information transfer but as a facilitative, motivational, and organizational process that helps farmers solve production problems, coordinate group action, access knowledge, and improve maize-based food-management practices. Evidence shows that extension and advisory services are associated with household welfare, food consumption, dietary diversity, and technology adoption when services are responsive to farmers' livelihood conditions (Aremu et al., 2025; Salam et al., 2024). Evidence from Indian Journal of Extension Education further supports this view, showing that extension contact was associated with food and nutrition security among farm households, while maize growers' marketing behavior was linked to planning, production, market information, extension contacts, and social participation (Gautam & Jha, 2022; Prasanna et al., 2024).

Farmer motivation is central because extension advice contributes to household outcomes only when farmers are willing and able to translate it into farming, storage, consumption, and livelihood decisions. Drawing on the ERG-based motivation framework described in contemporary organizational motivation literature, farmer motivation is conceptualized through existence, relatedness, and growth needs (Gibson et al., 2012). Existence needs reflect household food and income security, relatedness needs reflect social cooperation and farmer-group participation, and growth needs reflect learning, innovation, and improvement aspirations. These dimensions are relevant in semi-arid systems because farmers face livelihood risks, climate pressure, resource limitations, and food-security uncertainty (Swami et al., 2024; Touch et al., 2024). In addition, achievement motivation and management orientation have been shown to contribute significantly to occupational diversification among farmers, indicating that internal drive and managerial readiness are important behavioral resources for livelihood improvement (Jayasingh & Mishra, 2024). Therefore, motivation is treated in this study as a key internal condition that may strengthen farmers' capacity to use extension support for improving maize-based household food security.

Despite growing evidence on extension, farmer motivation, and smallholder food security, these components are often examined separately. Limited empirical attention has been given to how extension roles and ERG-based farmer motivation jointly explain maize-based household food security in semi-arid borderland farming systems. This is a conceptual gap because food security is shaped by external institutional support and farmers' internal readiness to secure food, cooperate socially, and improve food-management practices. This study examines two hypotheses: H1, the Role of Agricultural Extension is positively associated with maize-based household food security; and H2, farmer motivation is positively associated with maize-based household food security. By integrating extension roles, ERG-based motivation, and household food-security dimensions, the study contributes to a context-sensitive explanation of food security in semi-arid borderland agriculture.

METHODOLOGY

This study used a quantitative explanatory field design in Kupang, South Central Timor, and North Central Timor districts, East Nusa Tenggara Province, Indonesia, which represent semi-arid maize-farming areas along the Indonesia–Timor Leste border. The population comprised smallholder maize farmers whose livelihoods depended mainly on maize production. Systematic random sampling selected 300 respondents, and 244 valid cases were retained after excluding incomplete questionnaires and multivariate outliers. Data were collected from February to August 2025 using a structured questionnaire administered through face-to-face interviews. Participation was voluntary, informed consent was obtained, and respondent identities were anonymized. The final sample was adequate for CB-SEM, providing 24.4 cases per observed indicator.

The questionnaire was derived from a broader field instrument on maize farming, agricultural extension, farmer motivation, and household food security in Atoin Meto communities. This SEM analysis retained three latent constructs. The Role of Agricultural Extension was measured using 20 items grouped into facilitator-educator, technical-motivational, and organizer-linking roles, adapted from extension role frameworks (Wossen et al., 2017; Salam et al., 2024; Aremu et al., 2025). Farmer motivation was measured using 20 items grouped into existence, relatedness, and growth needs, based on Alderfer's ERG Theory studies (Gibson et al., 2012). Maize-based household food security was measured using 34 items grouped into availability, accessibility, stability, and utilization, adapted from FAO's food-security dimensions and household food-insecurity measurement (Coates et al., 2007; FAO, 2008). For SEM analysis, item scores were aggregated into 10 dimension-level composite indicators representing the three latent constructs. Agricultural extension and food-security items used a five-point frequency scale ranging from 1 = never to 5 = very frequent, while farmer-motivation items used a five-point willingness scale ranging from 1 = strongly unwilling to 5 = strongly willing.

Data were analyzed using IBM SPSS AMOS. CB-SEM with maximum-likelihood estimation was applied because the study tested a theoretically specified model and covariance relationships among latent constructs (Byrne, 2016; Kline, 2016). Data screening covered incomplete responses, multivariate outliers, and distributional assumptions. Confirmatory factor analysis assessed standardized loadings, squared multiple correlations, construct reliability, average variance extracted, discriminant validity, and model fit. Convergent validity was evaluated using loadings, construct reliability, and average variance extracted, while discriminant validity was assessed using the Fornell–Larcker

criterion, maximum shared variance, and average shared variance (Fornell & Larcker, 1981; Hair et al., 2021). The structural model estimated paths from agricultural extension and farmer motivation to household food security and the covariance between the exogenous constructs. Common method bias was reduced through anonymity, neutral wording, and construct separation, and was checked using Harman's single-factor test (Podsakoff et al., 2003).

RESULTS

Before evaluating the measurement and structural models, descriptive analysis was conducted to provide an initial overview of household food security, farmer motivation, and the Role of Agricultural Extension in the study area. This step was important to contextualize the empirical conditions of the main constructs before testing their statistical relationships in the SEM model.

As shown in Table 1, household food security was in the moderate/occasional category overall, with availability showing the highest score and stability showing the lowest score. This pattern indicates that maize availability after harvest was relatively strong, but year-round food stability, dietary utilization, and household purchasing capacity remained fragile. Farmer motivation was generally categorized as willing, although growth needs scored lower than existence and relatedness needs. This suggests that farmers' immediate concern for food and income security, as well as social cooperation, was stronger than their motivation for learning, innovation, and long-term improvement. The Role of Agricultural Extension was categorized as frequent, but the motivator role scored lower than the facilitator and organizer roles. These results indicate that extension services were present in the study area, yet they still need to strengthen motivational and organizational functions to support household food planning, maize stock management, post-harvest handling, and risk preparation.

These descriptive patterns support the need for structural analysis because the presence of extension services does not automatically translate into stronger food-security stability or growth-oriented motivation. Therefore, the SEM analysis examined how agricultural extension roles and farmer motivation were statistically associated with maize-based household food security, consistent with evidence that extension outcomes depend on farmers' livelihood conditions and their motivation to apply advisory support (Aremu et al., 2025; Swami et al., 2024).

Measurement model

Confirmatory factor analysis was conducted before structural interpretation to ensure that the latent constructs were measured adequately. Figure 1 presents the CFA measurement model, where rectangles represent observed indicators, ellipses represent latent constructs, and one-headed arrows represent standardized factor loadings. The figure shows that all observed indicators loaded strongly on their respective constructs, while the correlations among latent constructs indicate theoretically meaningful relationships without eliminating construct separation.

Figure 1 presents the CFA measurement model, showing that the Role of Agricultural Extension was represented by facilitator, motivator, and organizer roles; farmer motivation by existence, relatedness, and growth needs; and household food security by availability, accessibility, utilization, and stability. The CFA results showed strong standardized loadings for all indicators, ranging from 0.79 to 0.95 (Table 2). Extension indicators loaded between 0.93 and 0.95, farmer-motivation indicators between 0.90 and 0.94, and household food-security indicators between 0.79 and 0.87. These values exceeded commonly recommended thresholds and supported convergent validity (Kline, 2016; Hair et al., 2021).

The CFA results address the reviewer's concern about weak indicators. In the revised model, all indicators were retained because each loading was strong and theoretically consistent with its latent construct. This means that the extension construct no longer required cautious interpretation due to marginal measurement quality, and the measurement model provided a stronger basis for structural testing.

Table 3 confirms that all constructs met the recommended reliability and convergent-validity criteria. Construct reliability values were above 0.90, and AVE values exceeded 0.50 for all constructs. Therefore, the revised measurement model resolved the

Table 1. Descriptive statistics of research variables

Construct	Indicator	Mean	Score (%)	Category
Food security	Availability	4.31	86.24	Very frequent
Food security	Accessibility	3.66	73.16	Frequent
Food security	Utilization	3.00	60.08	Occasional
Food security	Stability	2.77	55.48	Occasional
Farmer motivation	Existence needs	3.94	78.73	Willing
Farmer motivation	Relatedness needs	3.66	73.17	Willing
Farmer motivation	Growth needs	2.97	59.49	Hesitant
Role of Agricultural Extension	Facilitator	3.57	71.40	Frequent
Role of Agricultural Extension	Motivator	3.37	67.40	Occasional
Role of Agricultural Extension	Organizer	3.50	70.00	Frequent
Total index	Household food security	3.22	64.36	Occasional
Total index	Farmer motivation	3.43	68.50	Willing
Total index	Role of Agricultural Extension	3.46	69.20	Frequent

Source: Authors' calculation from field survey data, 2025

Note: Score (%) = mean/5 x 100. Categories were based on equal intervals of the five-point scale: 20.00-36.00 = very low/very rare/strongly unwilling; 36.01-52.00 = low/rare/unwilling; 52.01-68.00 = moderate/occasional/hesitant; 68.01-84.00 = high/frequent/willing; and 84.01-100.00 = very high/very frequent/strongly willing. Category labels were adjusted to the construct being interpreted.

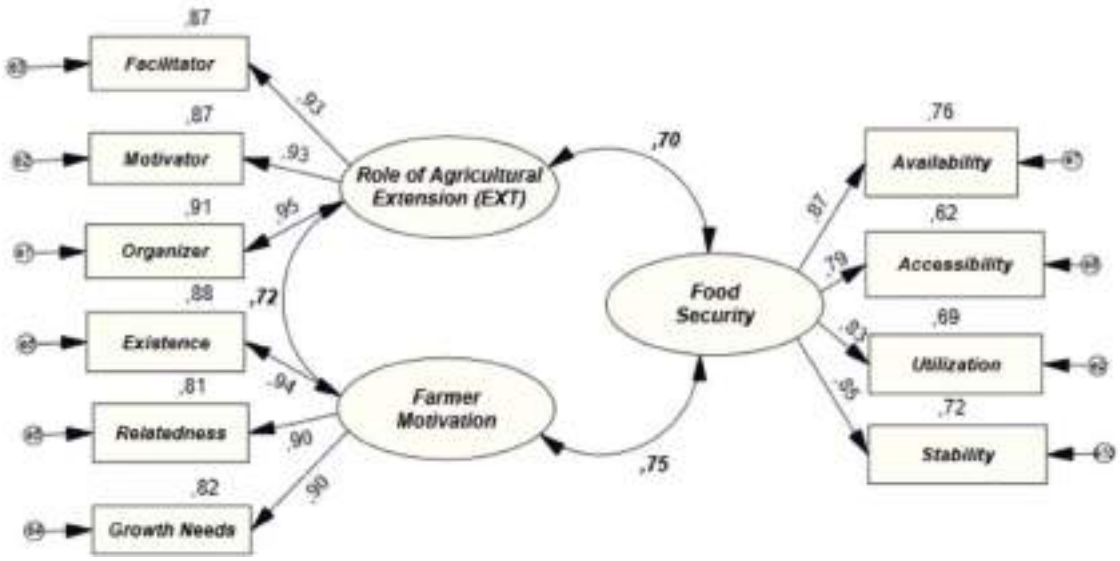


Figure 1. Confirmatory factor analysis measurement model.
Source: AMOS CFA output based on field survey data, 2025.; *Note:* Rectangles denote observed indicators, ellipses denote latent constructs, one-headed arrows denote standardized factor loadings, and curved two-headed arrows denote correlations among latent constructs.

Table 2. CFA standardized loadings and squared multiple correlations

Construct	Indicator	Loading	SMC	Decision
Role of Agricultural Extension	Facilitator	0.93	0.87	Accepted
Role of Agricultural Extension	Motivator	0.93	0.87	Accepted
Role of Agricultural Extension	Organizer	0.95	0.91	Accepted
Farmer motivation	Existence needs	0.94	0.88	Accepted
Farmer motivation	Relatedness needs	0.90	0.81	Accepted
Farmer motivation	Growth needs	0.90	0.82	Accepted
Household food security	Availability	0.87	0.76	Accepted
Household food security	Accessibility	0.79	0.62	Accepted
Household food security	Utilization	0.83	0.69	Accepted
Household food security	Stability	0.85	0.72	Accepted

Source: AMOS CFA output based on field survey data, 2025.
Note: One indicator for each latent construct was fixed to set the measurement scale; therefore, its standard error and critical ratio are not estimated in AMOS.

Table 3. Construct reliability and average variance extracted

Construct	Indicators	CR	AVE	Square root of AVE	Interpretation
Role of Agricultural Extension	3	0.956	0.877	0.937	Reliable and valid
Farmer motivation	3	0.938	0.835	0.914	Reliable and valid
Household food security	4	0.902	0.698	0.836	Reliable and valid

Source: AMOS CFA output and authors' calculation, 2025.
Note: CR = construct reliability; AVE = average variance extracted. CR >= 0.70 and AVE >= 0.50 indicate adequate reliability and convergent validity (Hair et al., 2021).

earlier concern about the extension construct and provided empirical support that facilitator, motivator, and organizer roles represent the Role of Agricultural Extension in this study.

Tables 4 and 5 show that the three constructs were empirically distinguishable. The square roots of AVE were higher than the inter-construct correlations, and AVE values exceeded both MSV and ASV. Although the correlations among EXT, farmer motivation, and food security were relatively high, the discriminant-validity results indicate that the constructs were related but not redundant. This supports the substantive argument that extension roles and farmer

Table 4. Fornell-Larcker discriminant-validity matrix

Construct	EXT	Farmer motivation	Food security
EXT	0.937		
Farmer motivation	0.72	0.914	
Food security	0.70	0.75	0.836

Source: AMOS CFA output and authors' calculation, 2025.
Note: Diagonal values are the square roots of AVE. Discriminant validity is supported when each diagonal value is greater than the relevant inter-construct correlations (Fornell & Larcker, 1981).

Table 5. AVE, MSV, and ASV for discriminant validity

Construct	AVE	MSV	ASV	Interpretation
Role of Agricultural Extension	0.877	0.518	0.504	Satisfied
Farmer motivation	0.835	0.562	0.540	Satisfied
Household food security	0.698	0.562	0.526	Satisfied

Source: AMOS CFA output and authors' calculation, 2025.
Note: MSV = maximum shared variance; ASV = average shared variance. Discriminant validity is supported when AVE exceeds MSV and ASV for each construct (Hair et al., 2021).

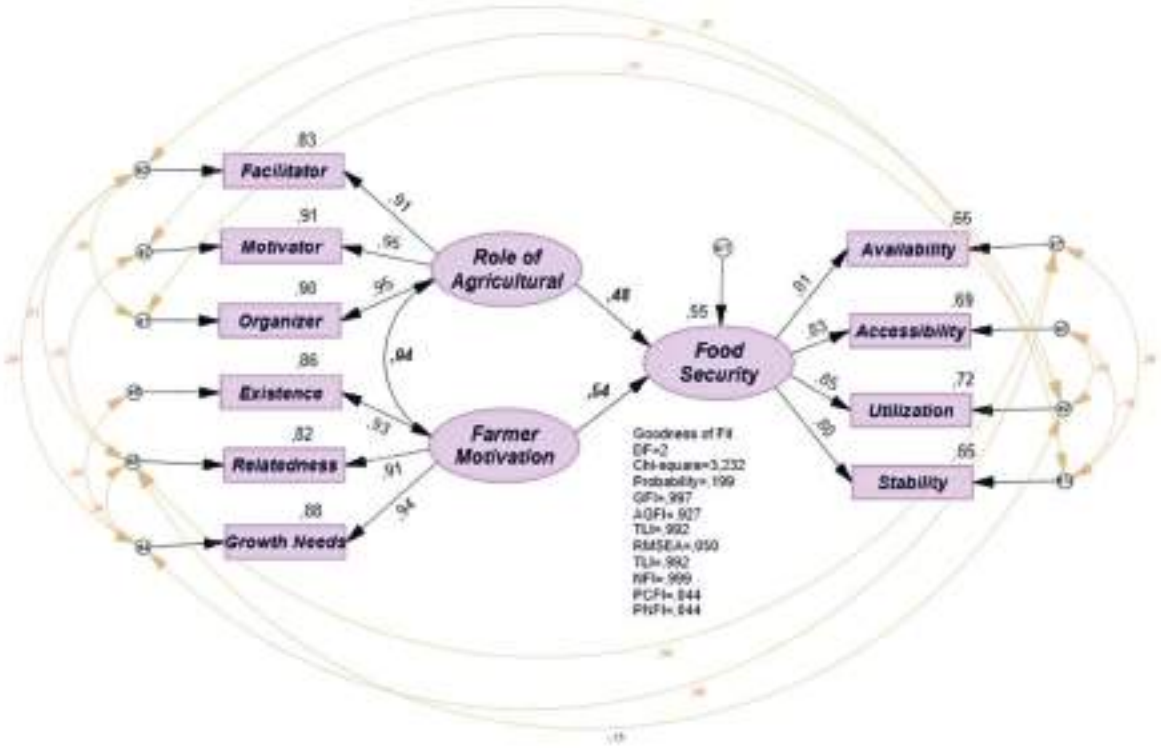


Figure 2. Final structural model after re-specification
Source: AMOS structural-model output based on field survey data, 2025.; *Note:* The diagram reports standardized estimates from the final model. Curved arrows represent covariance or residual-covariance adjustments among conceptually related indicators. Because the data are cross-sectional, the structural paths are interpreted as statistical associations rather than causal effects.

motivation are complementary but conceptually distinct components in explaining household food security.

Structural model and hypothesis testing

After theoretically defensible residual-covariance adjustments supported by model diagnostics and measurement logic, the final structural model was retained for hypothesis testing. The model specifies two direct paths to maize-based household food security: the path from the Role of Agricultural Extension and the path from farmer motivation. As shown in Figure 2, both paths were positive, and the model explained 55.0% of the variance in household food security, indicating moderate explanatory power for a household-level outcome shaped by ecological, economic, institutional, and behavioral factors.

The final model showed acceptable fit across absolute, incremental, and residual-based indices. However, because the model had only two degrees of freedom after respecification, the fit indices were interpreted cautiously and were not treated as evidence of a perfect model. Therefore, model adequacy was assessed using the combined evidence from several fit indices rather than relying on a single statistic. The detailed goodness-of-fit results are reported in Table 6.

The final model explained 55.0% of the variance in household food security and showed acceptable fit across absolute, incremental, and residual-based indices. Because the respecified model had only two degrees of freedom, fit indices and parsimony values were interpreted cautiously. The model was retained because the respecification was theoretically defensible, the measurement model was reliable and valid, and the structural paths were consistent with the hypotheses. Given the cross-sectional design, the paths were interpreted as statistical associations rather than causal effects. Hypothesis testing based on AMOS estimates showed that both hypothesized paths were positive and statistically significant at the 5% level (Table 7).

H1 was supported because the Role of Agricultural Extension was positively and significantly associated with household food

Table 6. Goodness-of-fit indices for the initial and final structural models

Index	Initial model	Final model	Criterion	Interpretation
df	32	2	Information	Degrees of freedom changed after respecification
Chi-square	327.130	3.232	p > 0.05	Substantial improvement
χ^2/df	10.223	1.616	d" 3.00	Fit in the final model
Probability	0.000	0.199	p > 0.05	Fit in the final model
GFI	0.759	0.997	>= 0.90	Fit in the final model
AGFI	0.586	0.927	>= 0.90	Fit in the final model
TLI	0.876	0.992	>= 0.90/0.95	Fit in the final model
RMSEA	0.195	0.050	<= 0.08	Fit in the final model
CFI	0.911	0.999	>= 0.90/0.95	Fit in the final model
NFI	0.904	0.994	>= 0.90	Fit in the final model
PCFI	0.648	0.044	Parsimony index	Low because df = 2
PNFI	0.642	0.044	Parsimony index	Low because df = 2
R2 food security	0.44	0.55	Higher value indicates greater explained variance	Explanatory power increased

Source: AMOS structural-model output based on field survey data, 2025.
Note: Fit indices were obtained from AMOS. The initial model was a benchmark, and the final model was used for hypothesis testing. Fit indices were interpreted cautiously because df = 2.

Table 7. Structural path estimates and hypothesis testing

Hypothesis	Structural path	Estimate	S.E.	C.R.	p-value	Standardized beta	Decision
H1	EXT -> food security	0.317	0.132	2.405	0.016	0.485	Accepted
H2	Farmer motivation -> food security	1.413	0.507	2.789	0.005	0.541	Accepted

Source: AMOS structural-model output based on field survey data, 2025.
Note: S.E. = standard error; C.R. = critical ratio. A p-value below 0.05 indicates a statistically significant association. The standardized beta values were used to compare the relative strength of the two paths.

security (standardized beta = 0.485; C.R. = 2.405; p = 0.016). This indicates that stronger extension roles as facilitator, motivator, and organizer were associated with higher maize-based household food security after accounting for farmer motivation. Substantively, extension contributes to food security by supporting problem solving, farmer-group coordination, access to relevant knowledge, and improved maize-farming and food-management practices. This finding is consistent with evidence that agricultural extension and advisory services are linked to household welfare, food consumption, dietary diversity, and technology adoption when services are responsive to farmers' livelihood conditions (Wossen et al., 2017; Rejula et al., 2017; Aremu et al., 2025; Salam et al., 2024).

H2 was also supported because farmer motivation was positively and significantly associated with household food security (standardized beta = 0.541; C.R. = 2.789; p = 0.005). The higher standardized coefficient indicates that motivation had a slightly stronger direct association with food security than extension. This suggests that household food security is shaped not only by external advisory support but also by farmers' internal readiness to secure food, cooperate socially, and improve farming and food-management practices. Existence needs may strengthen food and income security, relatedness needs may support cooperation through farmer groups, and growth needs may encourage learning, innovation, post-harvest improvement, and better household food management. This interpretation aligns with evidence that intrinsic motivation, perceived usefulness, institutional support, and knowledge capability influence farmers' willingness to adopt sustainable and adaptive agricultural practices (Gibson et al., 2012; Swami et al., 2024).

DISCUSSION

Overall, the findings show that maize-based household food security in the Indonesia–Timor Leste borderlands was associated with both agricultural extension and farmer motivation. Although extension services were perceived as relatively active, lower scores for food-security stability and growth motivation indicate that extension support has not been fully translated into year-round food stability and growth-oriented food-management behavior. Therefore, extension in semi-arid borderland systems should move beyond general technical advice and become more closely linked to maize stock management, post-harvest handling, household food planning, savings behavior, and dietary diversification. This interpretation is consistent with evidence that agricultural extension and advisory services improve household welfare, food consumption, dietary diversity, and farm outcomes when they are responsive to farmers' livelihood conditions and supported by farmer engagement, family resources, input use, and crop-management capacity (Salam et al., 2024; Aremu et al., 2025). It is also supported by evidence that household food and nutrition security is associated with resource-related and informational factors, including extension contact, and that maize growers require practical education, training, market information, and improved market access to strengthen production and marketing decisions (Gautam & Jha, 2022; Prasanna et al., 2024).

The stronger standardized association of farmer motivation with household food security provides the main conceptual contribution of this study. It suggests that advisory services are more meaningful when farmers have internal readiness to secure staple food, cooperate socially, and improve farming and household food-management practices. Existence needs strengthen concern for food and income security, relatedness needs support cooperation and mutual assistance, and growth needs encourage learning, innovation, post-harvest improvement, and dietary diversification. This finding supports studies showing that intrinsic motivation, perceived usefulness, institutional support, and knowledge capability influence farmers' adoption of sustainable and adaptive practices (Nain et al., 2007; Swami et al., 2024). It also aligns with evidence that achievement motivation and management orientation significantly contribute to farmers' occupational diversification, indicating that internal drive and managerial capacity are relevant for strengthening livelihood strategies (Jayasingh & Mishra, 2024). In semi-arid borderland households, food-security programs should therefore combine extension services with motivation-oriented strategies, particularly farmer-group learning, household food planning, maize storage improvement, cooperative support, and practical post-harvest management. Given the cross-sectional design, these implications should be interpreted as evidence-based associations rather than causal effects.

This study has several limitations. First, the cross-sectional design limits causal interpretation; therefore, the reported paths should be understood as statistical associations rather than definitive causal effects. Second, the use of self-reported questionnaire data may introduce recall bias and social desirability bias. Third, although model respecification improved the fit of the retained model, the modified structure requires further validation using independent samples, longitudinal data, or mixed-method designs. Finally, HTMT was not reported; however, discriminant validity was assessed using the Fornell–Larcker criterion and the AVE–MSV–ASV comparison, and future studies may complement these procedures with HTMT using item-level correlation matrices.

CONCLUSION

Agricultural extension and farmer motivation were positively and significantly associated with maize-based household food security among smallholder maize farmers in the semi-arid Indonesia–Timor Leste borderlands. Extension contributed through its facilitative, motivational, and organizational roles in supporting problem solving, farmer-group coordination, access to knowledge, and household food-management practices. Farmer motivation showed a slightly stronger direct association, indicating that food security is strengthened not only by external institutional support but also by farmers' internal readiness to secure staple food, cooperate socially, and pursue learning-oriented improvement. The study advances an integrated extension–motivation–food security model and extends the relevance of existence, relatedness, and growth needs to smallholder food-security research in vulnerable agrarian settings. Practically, food-security strategies in semi-arid borderlands should combine extension services with motivation-oriented approaches, especially farmer-group facilitation, post-harvest management, household food planning, and cooperative learning. Given the cross-sectional design, the findings indicate statistical associations rather than causal effects.

DECLARATIONS

Research ethics statement: The study protocol was reviewed and approved by the Research Ethics Committee of the Academic Hospital of Universitas Gadjah Mada (RSA UGM), Yogyakarta, Indonesia, under Ethical Clearance Number 032/RSA/KEP/EC/2026. The ethical review covered the research proposal, participant information sheet, and research questionnaire. The study was authorized in accordance with relevant national research ethics principles and the Guidelines and Standards for Research Ethics and National Health Development issued by the Ministry of Health of the Republic of Indonesia in 2021. Participation was voluntary, informed consent was obtained from all respondents before the interviews, and respondent identities were anonymized throughout data processing and reporting.

Conflict of interest: The authors declare that they have no conflict of interest. The research was conducted without any commercial, financial, or personal relationships that could be interpreted as influencing the design, implementation, analysis, interpretation, or reporting of the study.

Author contributions: Musa Frengkianus Banunaek contributed to conceptual development, field investigation, data collection, data curation, formal analysis, and preparation of the initial manuscript draft. Siti Andarwati contributed to methodology, validation, supervision, manuscript review, and editing. Sunarru Samsi Hariadi contributed to conceptualization, methodological guidance, validation, supervision, manuscript review, and editing. All authors reviewed and approved the final version of the manuscript and agreed to be accountable for the accuracy and integrity of the work.

Data availability: The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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Research Article

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Attitude of Paddy Farmers towards KVK Training Programmes: A Study of Trainees and Non-Trainees in Ariyalur District, Tamil Nadu

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HIGHLIGHTS

- This study compares the attitude of trainee and non-trainee farmers towards KVK training programmes; focusing on young farmers can increase participation and effectiveness.
- Trainees showed a more positive attitude towards KVK training programmes than non-trainees.
- The outcomes of this study can provide guidance to make KVK training more effective and encourage farmers' participation.

ARTICLE INFO

Keywords: Krishi Vigyan Kendra, Attitude, Trainee, Non-trainee, Socio-economic studies, Agricultural Extension, Rural sociology, Training impact.

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ABSTRACT

The study was conducted in Ariyalur district to assess, compare and identify the factors influencing the attitude of trainee and non-trainee farmers towards KVK training programme among paddy farmers. Krishi Vigyan Kendra (KVK), a district-level innovation hubs demonstrate practical agricultural research through on-farm trials, front-line demonstrations, and training programs. Farmers' attitude towards these trainings are key determinants of technology adoption and productivity. Positive attitudes are essential for the effectiveness and success of KVK training initiatives. The study followed an ex-post facto research design, includes 120 respondents (60 trainees and 60 non-trainees). Data were gathered in the year 2025-2026 using structured and pretested interview schedule. Analysed using frequency, percentage, Kendall's Tau correlation and stepwise regression. 55 percent of trainees had a highly favourable attitude, while 50% non-trainees exhibited a low attitude towards KVK training. Attitude was positively associated with education, scientific orientation information-seeking behaviour, and economic motivation and negatively with age, in both groups. Regression analysis identified information-seeking behaviour and training methods as key predictors for trainees, and education for non-trainees. The study concludes that training exposure significantly improves farmers' attitude, emphasizing the need for inclusive, need based strategies to enhance participation and adoption of improved agricultural practices.

INTRODUCTION

Krishi Vigyan Kendras (KVKs) are farm science centre introduced as a novel capacity building approach by ICAR, to enhance skills and knowledge in agriculture and allied disciplines among farmers, school dropouts, and grassroot extension personnel throughout India (Aparna, 2021; Ebrahim & Girija, 2020) and to quickly share new farming technologies with farmers (Samantaray et al., 2020). The first KVK was established on pilot basis at Pondicherry during 1974. KVK plays an important role in spreading agricultural technologies throughout India (Kumbhare & Khonde, 2009; Bharath et al., 2024) and are fully funded by the Indian

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government and linked with Agricultural Universities and ICAR institutes (Choudhary et al., 2025). KVK operates as decentralized, district-level agricultural innovation systems that facilitate the translational deployment of proven technologies through systematic on-farm assessment, adaptive refinement, and field-scale demonstration across heterogeneous micro-farming agro-ecological contexts (Ebrahim & Girija, 2020; Gayathri & Bonny, 2020). It demonstrates the practical use of scientific and technological innovations in agriculture by linking research with education at the grassroots, and serves as a 'lighthouse for farmers' across India. KVK functions as a knowledge dissemination and resource support centre for the farming community (Dey et al., 2023) and demonstrate new farming methods, train farmers and extension workers, and provide vocational training to rural youth (Mahato et al., 2020), helping to bridge the gap between technology development and its use by farming communities (Karak & Mukhopadhyay, 2020). KVKs play strong emphasis on the principle of learning through practical experience (Bar et al., 2015). The role of scientific staff in KVK is very crucial, vital and multifarious to address and support farmers in their decision process enabling them to achieve their goals of higher farm income (Sinha et al., 2021). KVK conducts vocational training programme in accordance with its mandated objectives (Singh et al., 2022) and organize numerous training programme, aiming to equip the beneficiaries with the skills and knowledge required to effectively carry out farming activities. These capacity-building interventions implemented significantly contribute to rural socioeconomic transformation by strengthening farm productivity, income diversification, and employment generation among farming community. To comprehensively assess the impact of KVK training programme, it is essential to examine trainees' orientation towards the training interventions, the extent of utilization of training inputs, and their preferences regarding various components and modalities of the training (Karak & Mukhopadhyay, 2020). Farmers' attitude towards agricultural training programs plays a crucial role in determining their level of participation, learning and adoption behaviour and are critical determinants of technology adoption and productivity enhancement. Research examining attitudes of trainees and non-trainees in KVK training activities which highlights the significant role of socioeconomic profiles in shaping attitudes and training outcomes (Swetank & Bose, 2024). Although KVKs have been studied for training effectiveness, several gaps remain. Most research focuses only on trained farmers or specific groups, with limited comparison to untrained farmers. There is insufficient investigation between trainees and non-trainees orientation toward training. Accordingly the study was carried out to Assess and compare the attitude of trainees & non-trainees towards KVK training programme, variables significantly influencing the attitude towards KVK training.

METHODOLOGY

The present study was conducted during the year 2025-2026 in Sembiyakudi, Karaippakam villages located in Thirumanur block and Venmankondan village, located in T. Palur block of Ariyalur district in Tamilnadu Sembiyakudi, Karaippakkam and Venmankondan villages were selected because more number of trainings were given to paddy farmers. Farmers in this area had greater exposure to KVK initiatives, making it suitable for studying the impact of training. The selection ensured reliable data on both trainee and non-trainee farmers. An ex-post facto design were used and as the variables of training exposure had already occurred. The study included 120 participants, comprising 60 trainees and 60 non-trainees. The trainees were selected through purposive sampling and non-trainees through random sampling method. With the help of the KVK officials, trainees' lists were prepared and data were collected from both trainees and non-trainees farmers in the same villages to ensure unbiased comparison. Primary data were collected from the structured interview schedule and secondary data from the KVK (Trainees list). Data were collected through the personal interview. The independent variables included Age, Educational status, Occupation, Farm sizes, scientific orientation, Risk orientation, Economic motivation, information seeking behaviour, experience, KVK training, KVK venue, training methods and season. Attitude towards KVK training programme served as the dependent variable and was measured using the scale developed by Medhi (2017) with suitable modification. Attitude scale consists of 20 statements and was measured using a three-point response pattern such as 3-point scale ("Agree" = 3, "Undecided" = 2, "Disagree" = 1) was applied for positive statements, and reversed for negative statements; respondents were then grouped into Low attitude (<=20), Medium (21- 40), and High (>40) levels of attitude. Data were gathered using a well-structured and pre-test interview schedule. The collected information was tabulated, coded and analysed using R Studio version (ggplot2 package). Frequency and percentage were used to describe the Socio-economic characteristic, Relationships between variables were analyzed using Kendall's Tau correlation, and while stepwise multiple regression determined the most influential variables affecting farmers' attitudes toward KVK training. The data were verified for completeness and accuracy before analysis. The findings were in a clear manner to withstand conclusion and it also provide suggestions that improve KVK training programme which leads to improve farmers livelihood and rural development.

RESULTS

The attitude of farmers towards KVK training was evaluated for the both trainee and non-trainee using frequency and percentage analysis in the Figure 1. It represents the frequency and percentage in both trainee and non-trainee. Among the trainees, thirty three respondents which is 55% exhibited a high level of attitude. This indicated majority of the farmers developed a strong positive attitude, mainly due to the direct exposure to KVK training activities, demonstration and information seeking behaviour. In addition, eighteen respondents (30%) of the trainees exhibited a medium level, moderate interest in KVK training programme. Only a small portion of trainees had low level of attitude, nine respondents (15%) which is individual differences such as limited participation and had less interest. Trainees had positive attitude towards KVK training programme. Among non-trainee, about half of the respondents which thirty (50%) showed a low level of attitude. It clearly shows that many of them were either unaware or not fully convinced about the benefits of KVK training programme. Around twenty two respondents which is 36.7%

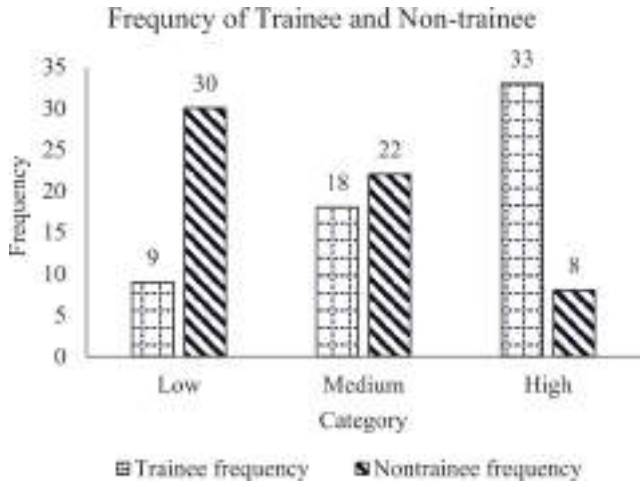


Figure 1. Level of attitude towards KVK training

grouped into medium category, they had minimum level of awareness. Only a small portion, eight respondents 13.3% shows a high level of attitude .The non-trainees had low level attitude towards KVK training programme. Overall it clearly shows that the trainees had inclined towards higher level of positive attitude, whereas non-trainees are more concentrated in the lower category. Training programmes play an important role not only in improving farmers' knowledge but also increase confident and motivation. While farmers had positive attitude towards KVK training, they will adopt an improved technology in paddy cultivation which leads to increased productivity and better farm income. This emphasizes the importance of continuous training and engagement to encourage positive perceptions and participation among farmers.

Relationship between Socioeconomic characteristic and attitude towards KVK training

Kendall's coefficient of correlation was applied for both trainees and non-trainees to assess the relationship between socio-economic characteristics and attitude (Figure 2 and 3)

In Figure 2, for trainees, correlation analysis revealed that education, risk orientation, economic motivation, and information-seeking behaviour were positively related to attitude at a highly significant level (1% probability). Training venue, training methods, and season also showed a significant positive association with attitude, while Farm size showed a positive relationship with attitude, significant at the 5% level. Age demonstrated a significant negative relationship, whereas occupational status showed no significant association with attitude. Improving education, risk taking ability, strengthening economic motivation and promoting information seeking behaviour enhance farmers' positive attitude towards KVK training. Proper planning of training venue, methods and season also positively influences attitude.

In the Figure 3, among untrained farmers, Kendall's correlation analysis showed that educational status, scientific orientation, risk orientation, economic motivation, information-seeking behavior, farming experience, and season of training were positively and significantly associated with attitude toward KVK training at the 1% probability level. In contrast, age demonstrated a significant negative relationship with attitude, while occupational status and farm size were not significantly related. In both the groups result shows that education, risk orientation, economic motivation and information seeking behaviour are positively related to attitude towards KVK training programs, Season of training is also positively associated both the trainees and non-trainees. Age consistently had

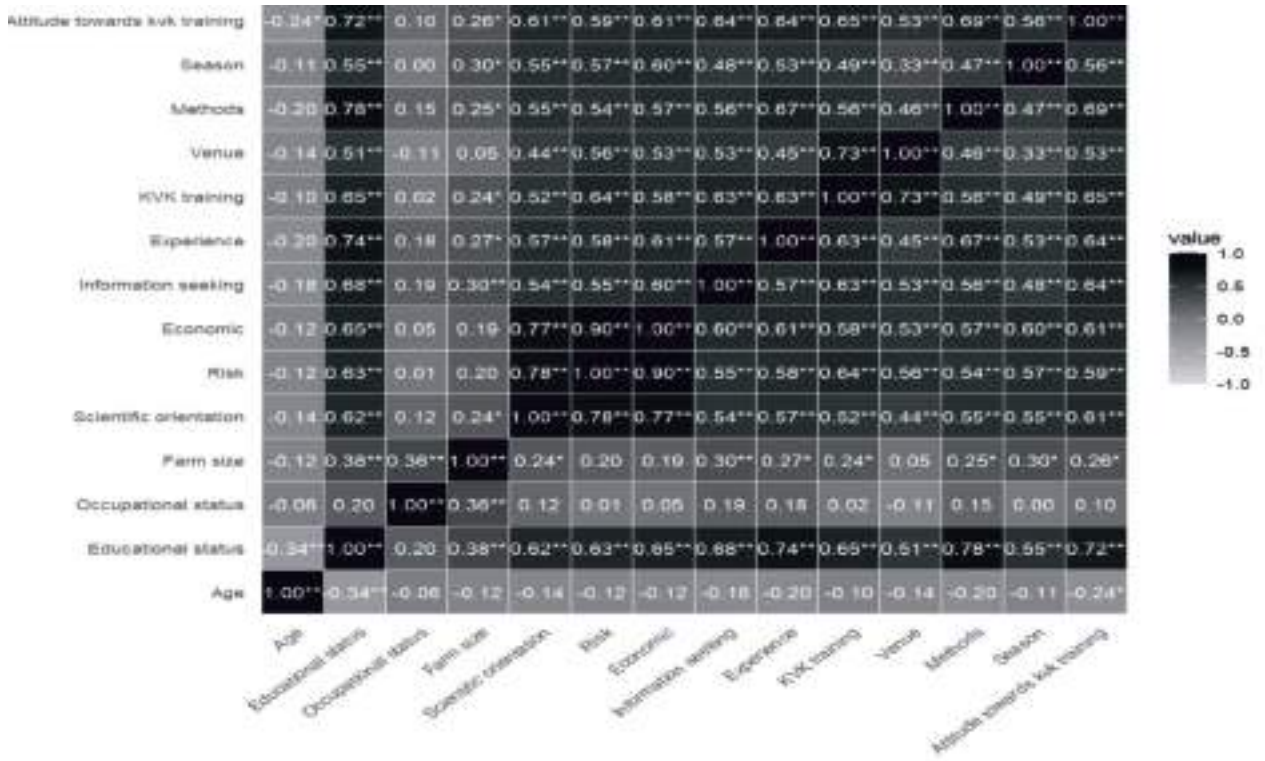


Figure 2. Relationship between Socioeconomic characteristic and attitude of Trainees' towards KVK training

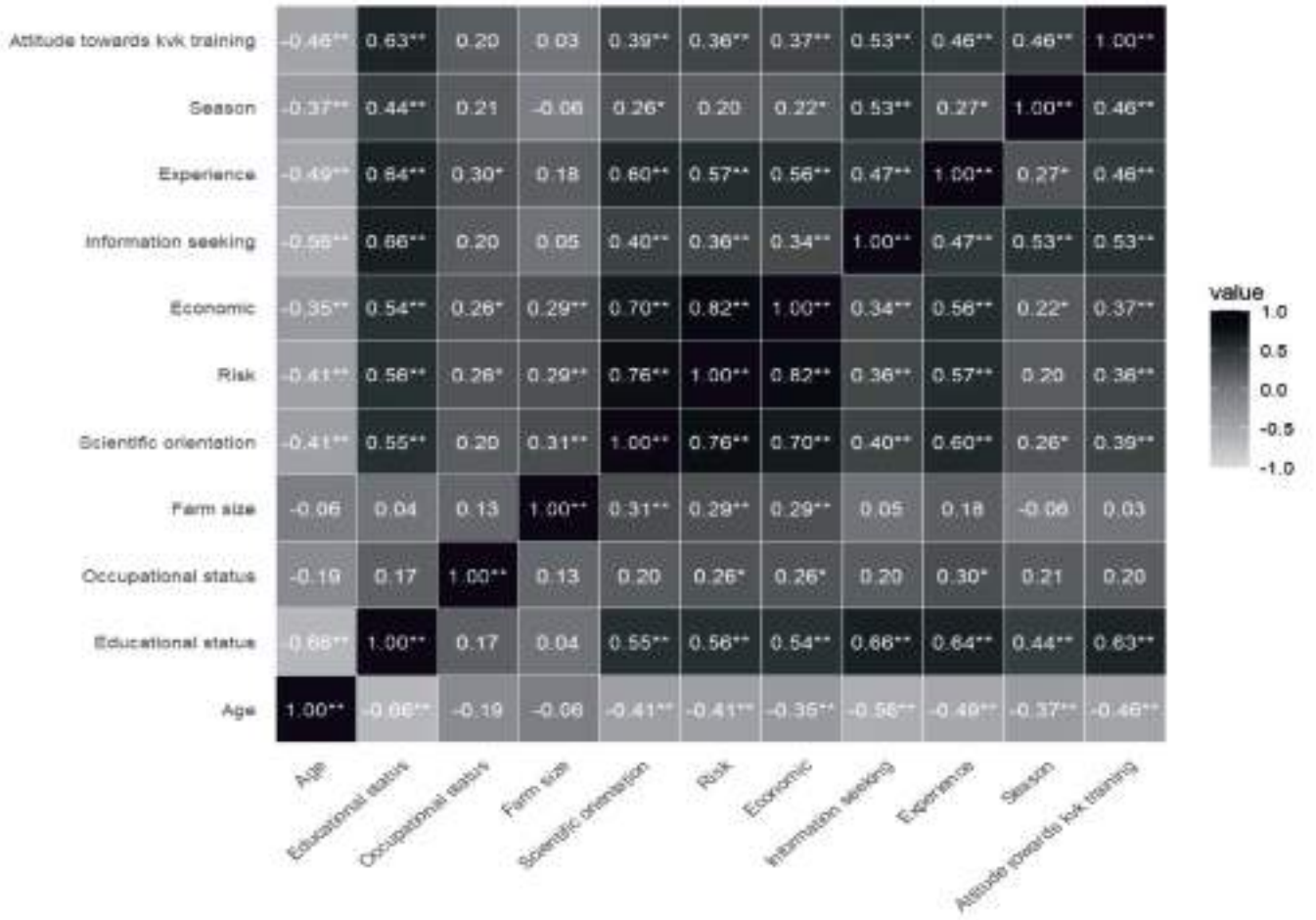


Figure 3. Relationship between Socioeconomic characteristic and attitude of Non-trainees towards KVK training

a negative influence, indicating that older farmers may require additional encouragement or support. Occupational status showed no significant impact in either group, emphasizing that other personal and training-related factors are more important in determining attitudes.

Key factors influencing farmers' attitude towards KVK training

Stepwise regression analysis

In table 1, the stepwise regression model accounted for a substantial portion of the variation in attitude, with an R^2 of 0.823 and an adjusted R^2 of 0.817, indicating that approximately 82% of the differences in attitude were determined by the variables in the model. Information seeking behaviour (X_8) and KVK methods (X_{12}) were found to have a strong positive predictors that influences the attitude towards KVK training programme. Farmers who actively gather information sources, followed the KVK recommendations and participated in the training sessions exhibited positive attitude towards KVK training. In addition, economic motivation and risk orientation also showed an influence and was relatively lower compared to information seeking behaviour and training methods . For non-trainees, the regression analysis found that moderate level of explanatory power, with an R^2 value of 0.615 and an adjusted R^2 of 0.645. The regression equation $Y= 23.315 + 3.194\ X_2$ indicated that education as a key influencing factor which is 61% of variation in farmers' attitude. This finding highlights the importance of education as the key factors influencing farmers' attitude .Farmers with higher education more likely to collect the information and adopt the newly improved practices. Thus, to develop a more positive attitude towards KVK training, the overall result clearly show that both training related factors and individual characteristic play role in determining farmers' attitude. Active participation in training, along with the strong tendency to seek information enhances the effectiveness of training programme by building confidence and interest among farmers. At the same time education acts as a crucial factor in shaping positive attitude towards training among non-trainee farmers. These finding revealed that the improving access to information, strengthening training methods in trainees and education in non-trainees collectively increase farmers' positive attitude.

Table 1. Regression equation

	Regression Equation	R Square	Adj R Square
Trainee	$Y= -3.19 + 0.167\ X_8 + 2.25\ X_{12}$	0.823	0.817
Non-trainee	$Y= 23.315 + 3.194\ X_2$	0.615	0.645

{X_8-information seeking behaviour, X_{12} - KVK methods, X_2-Educational status, Y-Attitude towards KVK training}

DISCUSSION

The finding showed a difference in attitude between trainee and non-trainee farmers towards KVK training programme. Frequency and percentage analysis indicated that more than half of the trained farmers had positive attitude. In contrast, large proportion of non-trainees farmers showed a lower level attitude Overall, a large proportion of trained farmers had a positive attitude compared to non-trained farmers towards KVK training programme. Similar of the findings reported by (Nain & Chandel, 2010; Swetank & Bose, 2024). This difference was mainly due to their exposure to training programme, demonstrations and interaction with KVK scientists. Similar finding reported by (Singh et al., 2023). Such exposure helped farmers understand the benefits of improved agricultural technologies and the practical usefulness of training in solving farm problems. Positive attitude helps to increase in adoption of newly improved technology which leads to higher yields and increased income and improves farmers' livelihood. Kendall's Tau Correlation revealed that education, scientific orientation, economic drive and information-gathering behaviour were positively and showed a significantly related to farmers' attitudes toward KVK training programs. This is consistent with the findings of (Geethu & Bindu, 2019; Nath et al., 2025). In addition planning of training aspects like training venue, methods and season further enhance farmers' attitude towards KVK training programme. Farmers with higher education understood the importance of modern farming practices and training programme better. The similar type of findings also found in (Nain & Trikha, 2009; Mishra & Mazhar, 2024). Similarly, farmers who actively searched for agricultural information and had strong economic motivation showed more interest in training activities that could improve their productivity and income. Age showed a negative relationship with farmers' attitude in non-trainee and trainee. Thus the old age farmers had high number of participation. Involving the young farmers by giving awareness and motivation to participate in KVK training programme. Younger farmers were more willing to learn new methods, while older farmers depended more on their traditional farming practices. But while participating in KVK training programme, older farmer gathered information and adopted a newly improved agriculture practices. Increasing youth participation will further enhance outcomes. The regression analysis showed that information-seeking behaviour and training methods were the main factor influencing the attitude of trained farmers. Which gives an 82% contribution to increasing in attitude towards KVK training programme.This indicated that farmers who regularly accessed agricultural information and attended well-organized training programme developed a more favourable attitude towards KVK activities. Also economic motivation and risk orientation can enhance the attitude at the minimum level and also other variables gives 100% contribution. Among non-trained farmers, education was found to be the most important factor influencing their attitude towards KVK training programme which is 61% of the variation and targeting non-trainee farmers with lower educational levels to enhance overall participation and attitude. Education farmers can access, understand and apply newly improved practices. Non-trainee faced barriers to participation such as lack of awareness, limited access to training programs, economical constraints and time constraints. In contrast, Training programme gives a greater confidence, risk taking ability, economical motivation, gathering information and experimenting with the new innovation techniques. Moreover, learned skills allowing farmers to resolve problems and making confident decision in agriculture practices. Well planned training sessions, considering appropriate venues, duration and seasonal timing encourage active participation and positive learning environment. These findings suggest that combining effective training methods and information access strengthens the impact of KVK training methods, making farmers more in adopting new innovation practices.

CONCLUSION

The study shows that trained farmers' have a more positive attitude towards Krishi Vigyan Kendra training programme than non-trained farmers. Training programme should be made need based, more practical oriented, modern teaching methods and interactive learning approaches, can further improves farmers' understanding and interest. Overall improving accessibility, relevance and engagement in Krishi Vigyan Kendra training programme will be crucial for developing positive attitude among farmers' and enhance their active participation in an agriculture development initiative. Strengthening these initiative can help farmers adopt recommended practices more confidently, thereby improving productivity, sustainability and overall agriculture development in rural communities.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the respondents and their organisations regarding the study during the course of the data collection.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The author declares that they have thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Article

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Gendered Patterns and Prevalence of Internet Use among Adolescents: Evidence from Varanasi, India

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HIGHLIGHTS

- Smartphone and internet penetration were high across genders, and no significant gender differences were observed, indicating equal digital accessibility for males and females.
- Males preferred internet to use online gaming and making public social media profiles, whereas females preferred to use it for education, social media, and for news consumption.
- YouTube and WhatsApp were the most popular applications among the respondents. However, Facebook and Twitter showed significant gender disparity among respondents.

ARTICLE INFO

Keywords: Internet, Adolescents, Gender, YouTube, Social media.

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ABSTRACT

The rapid expansion of internet access has profoundly influenced adolescents' daily routines, revealing emerging differences in usage patterns based on gender. The purpose of this study was to investigate the gender difference in internet usage patterns and its frequency. This cross-sectional descriptive study was conducted among nine senior secondary schools in the Varanasi district. The study administered a questionnaire containing closed-ended questions. The survey was conducted from March 2024 to August 2024 among randomly sampled 200 students aged 15 to 18 years. It was found that smartphone ownership was high among both male (94.1%) and female (88.9%) participants. YouTube and WhatsApp emerged as the most preferred applications for both genders. Males were more likely to have public social media accounts compared to females, and they share photos and videos on them. Males were significantly more engaged in online gaming, while females showed higher engagement in social media, online chatting, educational activities, and news. Binary logistic regression analysis further revealed that gender significantly predicted engagement in online gaming, with males more likely to participate. The study highlights notable gender disparities in Internet usage patterns, focusing on the intensity of use. These results emphasize the necessity of gender-sensitive digital literacy programs and policy measures to encourage adolescents to use the internet in balance way.

INTRODUCTION

Over the past two decades, there has been a significant and rapid rise in the use of the internet across all social demographics, particularly among adolescents and young adults (Bickham, 2021). The World Bank reported that 46.31% of the population in India was using the internet in 2021, which increased to 55% (821 million users) in 2023 (Internet & Mobile Association of India, 2023). The penetration of the internet in India was just 14% in 2014; however, over the past decade, the number of internet users has quadrupled, positioning the country as the second-largest in the world in terms of active internet users by 2024 (Statista, 2024). Recent projections

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suggest that India is expected to surpass 900 million internet users by 2025, with adolescents and young adults constituting the largest user group. Globally, seventy-nine percent of the population aged 15-24 years uses the internet, which is 14% higher than the remaining population (65%). Across all regions of the world, a consistent generational digital divide has been observed over the past four years (International Telecommunication Union, 2023).

The internet has become a crucial element of individuals' education, professional endeavours, and daily existence, largely due to the extensive integration of internet technology, and this effect is particularly evident among young people (Joshi et al., 2022). As technological advancements continue to reshape lifestyles, they also exert significant influence on mental well-being. Although these advancements have facilitated information access and communication, they have concurrently contributed to an increase in psychological concerns associated with excessive internet use (Scott et al., 2017). The widespread adoption of smartphones, social networking platforms, online gaming, and instant messaging has rendered the internet an integral component of young people's lives (Stavropoulos et al., 2021). Research conducted across Western and Asian contexts suggests that the younger generation is increasingly vulnerable to Problematic Internet Use (PIU) (Tomczyk & Solecki, 2019). Researchers frequently observe that individuals exhibiting addictive patterns demonstrate symptoms such as irritability, aggression, conduct disorders, obsessive–compulsive tendencies, and depression (Kaur & Dhillon, 2021). The Diagnostic and Statistical Manual of Mental Disorders (DSM-5-TR) and the American Psychiatric Association, 2022 recognize gaming disorder as a behavioural addiction. Adolescents who excessively engage with the internet without adequate regulation are emerging as a significant concern due to the potential adverse impacts on their emotional, social, and academic well-being (Mishra et al., 2024). Research indicates that excessive use of digital devices may hinder students' ability to concentrate in class and diminish their motivation for achievement (Yadav and Dube, 2025). Evidence suggests that increased screen time is negatively associated with participation in outdoor activities, completion of household responsibilities, and the ability to disengage attention from digital screens (Gupta & Vatta, 2025). Gender-based differences in digital behaviour are particularly important, as they may influence both exposure to online opportunities and vulnerability to potential risks. The present study aims to examine the gendered patterns and prevalence of internet use among adolescents. Specifically, it seeks to explore variations in frequency, purpose, and duration of internet use between male and female users. Identifying these gender-based differences in digital behaviour is essential in the contemporary digital era to promote balanced internet engagement and foster healthier relationships with technology among adolescents.

METHODOLOGY

Built upon existing viewpoints, present study intended to gain a deeper understanding of internet usage pattern and prevalence among adolescents of Varanasi, India. A closed-ended questionnaire was prepared and the content validation had been done through the experts. The questionnaire was comprised of twenty-two items focusing on various dimensions of internet usage patterns. This cross-sectional field study employed a stratified random sampling method for data collection to ensure adequate representation of relevant subgroups within the population. The strata were established based on school type (government and private) and gender (male and female).

The study targeted adolescents aged 15-18 years, a critical stage of late adolescence characterized by increased independence and identity formation, alongside active digital technology usage. The study focused on regular internet users, particularly adolescents, who were considered vulnerable to the effects of internet use and the development of long-term digital habit. The Varanasi district was selected for the study location. Due to the distinctive sociocultural and demographic makeup, which includes a mix of urban, rural, and semi-urban inhabitants. The survey was conducted from March 2024 to August 2024 including 200 adolescents attending nine secondary schools in Varanasi, Uttar Pradesh, India. An informed consent was obtained from the school principals and students for their voluntary participation in this study. The study was split into two parts: Initially participants read the information sheet, provided informed consent, and completed the demographic details. Subsequently, they responded to questions related to their internet-related behaviours. Efforts were made to maintain anonymity and confidentiality of the participants throughout the data collection process to encourage honest and unbiased responses. Data were entered into Microsoft Excel spreadsheet and analysed using the Statistical Package for the Social Sciences (SPSS, V.24.0). To compare variables among groups, the chi-square (χ^2) test was employed at a significance level of $p \leq 0.05$ to examine associations between gender and internet usage pattern. Descriptive statistics such as standard deviation and mean were used in this study.

The comprehensive demographic analysis was crucial for placing the results in perspective and understanding the potential effect of variables such as educational level, age, gender, and residential area on the study results. Among 200 participants, the number of male and female respondents was almost equal, as there were 50.5% males (101) and 49.5% females (99), respectively. The educational level comprised mainly tenth-class students (38.8%); 27.3% of respondents were from eleventh class, 20.4% were from twelfth, and the least representation was from ninth class (13.4%). This balance between high school and twelfth (senior secondary) students provides a robust foundation for examining educational influences on the variables of interest. The largest proportion of participants were 15 years old (38.3%), followed by those aged 16 years (25.8%). Adolescents aged 18 years constituted 19.4% of the respondents, while 17-year-olds represented the smallest proportion (15.9%). This distribution indicates a higher concentration of mid-adolescent respondents in the study sample. The residential area data reveals an almost even split between city and rural respondents, with 40.2% from city areas and 39.8% from rural areas. The remaining 19.4% are from towns. This distribution allows for an examination of how geographic location might influence the study variables, providing insights into potential urban-rural disparities.

RESULTS

The smartphone ownership was high among both male (94.1%) and female (88.9%) participants. The chi-square test indicated that

Table 1. Smartphone ownership in relation to participants' demographic details

Demographic characteristics	Yes (%)	No (%)	Total	χ^2/P-value
Gender				
Male	95 (94.1)	6 (5.9)	101 (50.5)	1.71/0.190
Female	88 (88.9)	11 (11.1)	99 (49.5)	
Class				
9th	21 (80.7)	5 (19.2)	26 (13)	
10th	66 (84.6)	12 (15.4)	78 (39)	.324/0.000
11th	55 (100)	0 (0)	55 (27.5)	
12th	41 (100)	0 (0)	41 (20.5)	
Age				
15	62 (80.5)	15 (19.4)	77 (38.5)	
16	50 (96)	2 (4)	52 (26.5)	
17	32 (100)	0 (0)	32 (16)	
18	39 (100)	0 (0)	39 (19.5)	
Residential area				
Rural	72 (90)	8 (10)	80 (40)	
City	75 (91.4)	7 (8.6)	82 (41)	0.743/0.690
Town	36 (94.7)	2 (5.3)	38 (19)	

there were no statistically significant differences in smartphone ownership across gender, educational status, age-group and their residential area. Almost all participants used smartphones to access the internet, either their own device or a shared device. Only three students reported having laptops, but they commonly utilize smartphones.

Table 2. Gender-based distribution of respondents about their daily usage of social media applications

Social media apps	Male (N=101)	Female (N=99)	*χ^2/P-value*
YouTube	99	95	*1.90/0.167*
Instagram	61	51	*1.60/0.206*
Snapchat	41	35	*.583/0.445*
Facebook	48	21	*15.31/.001*
WhatsApp	100	96	*1.06/0.303*
Twitter (Now X)	31	18	*4.24/0.039*

Table 2 represents how many social media apps the respondents used daily. YouTube and WhatsApp were the most frequently used applications by the respondents. Both male and female respondents exhibited similar engagement levels with this video-sharing platform, as there was no significant difference in male users and female users (χ^2=1.90, *P=0.167)*. Instagram and snapchat usage also showed no significant gender difference (χ^2 = 1.60, p = 0.206, χ^2 = 0.583, p = 0.445) respectively. In contrast, Facebook usage demonstrated a significant gender disparity (χ^2 = 15.31, p < 0.001). Males were more frequently engaged in Facebook than females, indicating a pronounced gender difference. A significant gender difference was also observed in Twitter (now X) usage (χ^2 = 4.24, p = 0.039).

The cross-tabulation of favourite apps by gender (Figure 1) revealed distinct patterns in app preferences, reflecting both gender-based variations and potential implications for content targeting and

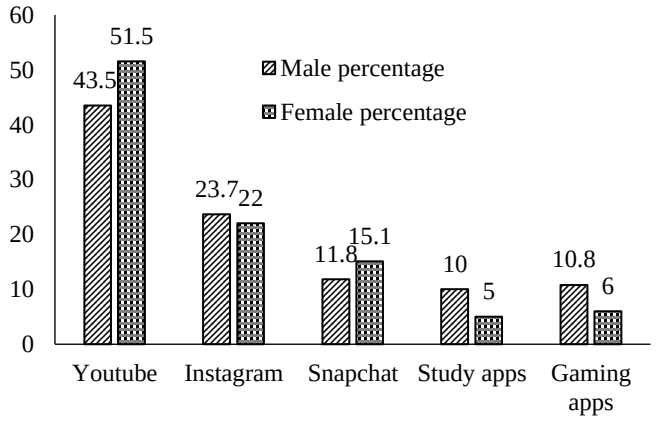


Figure 1. Relationship between favourite app and gender

user engagement strategies. YouTube emerged as the most preferred app among both genders, with 43.5% of males and 51.5% of females identifying it as their preferred platform. Instagram exhibited a fairly balanced preference across genders, with 23.7% of males and 22% of females selecting it as their favourite app. Snapchat, on the other hand, displayed a slight gender disparity, with 11.8% of males and 15.1% of females favouring the app. In contrast, online learning applications revealed a more significant gender difference, with 10% of males and only 5% of females reporting them as their preferred apps. Gaming Apps also displayed a notable gender-based preference, with 10.8% of males and 6% of females choosing them as their favourite.

The chi-square test results (Table 4) indicated a significant difference in social media usage patterns between genders (χ^2 = 14.49, p ≤ 0.001). Males were more likely to have public social media accounts and share photos and videos compared to females. A significant difference was observed across educational levels (χ^2 = 37.12, p ≤ 0.000). Students from higher (11th and 12th grades)

Table 3. Privacy Settings of Social Media Accounts and Photo/Video Sharing Behaviour

Demographic characteristics	Public and share	Private and do not share	No social media account	χ^2/P-value
Gender				
Male	88	6	7	14.49/0.001
Female	70	25	4	
Class				
9th	21	6	0	
10th	45	22	10	
11th	52	3	0	37.12/0.000
12th	41	1	1	
Age-group				
15	42	27	8	
16	47	3	2	49.66/0.000
17	31	0	1	
18	38	1	0	
Residential area				
Rural	65	13	2	
City	66	9	7	5.82/.213
Town	27	9	2	

Table 4. Relationship between gender and purpose to use the internet

Purpose to use the internet	Male (%) (101)	Female (%) (99)	χ^2/*P-value*
Online game	56.4	24.2	*21.5/0.001*
Chatting/sending mail\messages	63.3	72	*3.37/0.185*
Online Banking	29.7	39.3	*3.26/0.196*
Social media	35.6	57.5	*11.15/0.004*
Watching reels/shorts	64.3	65.5	*0.037/0.84*
Listening music\watching videos	75.2	80.8	*2.22/0.32*
To gain subject knowledge	71.2	83.83	*6.21/0.04*
To gain knowledge beyond the subject	43.5	58.5	*5.88/0.05*
News	28.7	43.5	*6.63/0.03*
Making new friends	36.6	34.3	*1.10./0.57*
Porn videos	8	8	*1.02/0.59*

classes, were more likely to maintain public accounts and actively share content, while students from lower (9th and 10th) classes showed comparatively restricted sharing behaviour. Significant differences were noted across age (χ^2 = 49.66, p ≤ 0.000). Adolescents aged 16 and above demonstrated a greater inclination toward public accounts and content sharing, whereas younger adolescents were more likely to keep accounts private or not use social media platforms. The analysis of residential area showed no significant difference in social media usage patterns (χ^2 = 5.82, p = 0.213). While city and rural residents exhibited a slightly higher tendency towards public accounts compared to those in town areas, this difference was not statistically significant.

The table provides an understanding of the relationship between gender and various purposes of using the internet. The analysis revealed a significant gender disparity in online gaming (χ^2 = 21.5, p ≤ 0.001). Males were more inclined than females in using the internet for gaming. The purpose of chatting or sending messages did not show a significant gender difference (χ^2 = 3.37, p = 0.185). Both males and females were engaged in online communication at similar rates. A significant gender difference was observed in social media usage (χ^2 = 11.15, p ≤ 0.004), with females more likely to engage with social media platforms than males. There was no significant difference between males and females when it comes to watching reels or shorts (χ^2 = 0.037, p = 0.84). There was also no significant gender difference in listening to music or watching videos (χ^2 = 2.22, p = 0.32). The use of the internet to gain subject knowledge revealed a significant gender difference (χ^2 = 6.21, p dd 0.04), with females (83.8%) more likely than males to use the internet for educational purposes. There was a significant gender difference in using the internet to gain knowledge beyond the subject (χ^2 = 5.88, p ≤ 0.05), with females more likely than males to engage in this activity. News consumption demonstrated a significant gender difference (χ^2 = 6.63, p ≤ 0.03), with females more likely than males to use the internet for news. The purpose of making new friends showed no significant gender difference (χ^2 = 1.10, p = 0.57). Both males and females used the internet for social networking to similar extents. Finally, the use of the internet for watching pornographic content revealed no significant gender difference (χ^2 = 1.02, p = 0.59). Both males and females reported similar levels of engagement in this activity.

Binary logistic regression analysis was conducted to evaluate the predictive significance of gender and age in adolescents about internet gaming. The model had statistical significance overall (χ^2 = 13.859, p = .001), indicating that the predictors collectively contributed to distinguishing between adolescents who engaged in online gaming compared to those who did not. The model accurately classified 65.6 percent of the cases. Gender emerged as a significant predictor of online gaming activity (B = -1.414, p < .001). The odds ratio demonstrated that male adolescents were around four times more likely to engage in online gaming than their female counterparts. Nonetheless, age was not a substantial predictor of online gaming behaviour (B = 0.168, p = .507). The results demonstrated that gender significantly influence adolescents' participation in online gaming, although age did not substantially affect involvement in the studied population.

DISCUSSION

The research shows considerable gender differences in internet usage patterns, focusing on purpose of usage and types of online activities among respondents in Varanasi. The study includes a diverse educational distribution of participants is significantly diverse, representing a wide range of academic proficiency levels, which is critical for interpreting the study's findings. The balanced gender distribution mitigates potential biases and enhances the generalizability of the results. Additionally, the inclusion of urban, semi-urban and rural respondents provides a nuanced view of how geographic factors may interact with internet use and related behaviours. Smartphones are the predominant means of internet access, with no respondents claiming non-usage. John et al., 2024 also found the same result in Indian rural secondary school going adolescents that they had the accessed to smartphone for internet use rather than other devices. Statistical analysis revealed no significant difference in ownership of smartphone between male and female users (χ^2= *1.71, P= .190*), as well as in residential area (χ^2=*0.743, P= 0.690*) supporting findings from Hargittai and Marwick (2016) regarding minimal gender differences in smartphone ownership among young adults in the U.S. However, other research, such as that by Lopez-Fernandez (2017), suggests that gender disparities in smartphone ownership may vary in different cultural contexts. Moreover, a significant and positive correlation was

Table 5. Binary logistic regression analysis predicting adolescents' engagement in online gaming from gender and age

Variable	B	S.E.	Wald	p-value	Odds Ratio (Exp(B))
Gender (Male)	-1.414	0.395	12.841	< .001	0.243
Age	0.168	0.253	0.441	.507	1.183
Constant	0.936	0.471	3.949	.047	2.550

Note: B = regression coefficient; S.E. = standard error; Exp(B) = odds ratio.

identified between owning a smart phone and age group (χ^2=*20.98, p=.000)* as with increasing age, ownership of smartphone was also increasing. Previous studies link smartphone ownership to negative outcomes, such as psychological distress and problematic usage (Chen et al., 2021), suggesting minors with personal devices report more adverse incidents (Martín-Cárdaba, 2024). The study identified YouTube and WhatsApp emerged as leading social media apps, followed by Instagram, Snapchat, Facebook, and Twitter following behind. This aligns with results showing heightened YouTube usage among 16- to 20-year-olds and increased Instagram engagement as compared to other platforms, as noted by Alhabash and Ma (2017) and Mahendran et al. (2024).This study reveals a shift in platform preference, with YouTube and WhatsApp emerging as the most preferred platforms among adolescents, illustrating shifts in social media usage over time in consistent results with Zimmermann, et al. (2020). In contrast, Pandey et al. (2020) stated that nearly all adolescents used WhatsApp, Facebook, and several other applications, often using various digital platforms simultaneously. This study also highlighted notable gender differences in Facebook and Twitter usage, with males showing higher engagement levels. This pattern implies that teenagers are moving toward more visually oriented and newer platforms (such as YouTube, Instagram and Snapchat) and moving from older platforms (such as Facebook and Twitter) to the margins of their social media usage (Pew Research Centre, 2023). Male adolescents exhibit distinct patterns in social media use, characterized by public account maintenance and high online gaming activity. These behaviors reflect gender socialization, with boys drawn towards technology and competitive play in digital environments (Prakash, 2025). In contrast, female adolescents focus more on communication, internet chatting, learning, and accessing news, indicative of academic socialization influenced by their restricted real-world mobility, particularly in India (Prakash, 2025). Digital platforms thus emerge as crucial spaces for these forms of interaction and information gathering. This phenomenon aligns with the concept of the second-level digital divide, emphasizing not just access to technology, but also the varied utilization of digital resources among different gender groups (Iqbal, 2021). The study supported previous findings indicating that girls score higher in social media communication, while boys excel in gaming (Svensson et al., 2022). Although some online activities, such as chatting and short-form video viewing, highlighted no significant gender differences. Understanding these patterns provides valuable insights into how different genders interact with digital platforms and can inform the development of targeted content and services.

CONCLUSION

The study provides empirical data regarding patterns and prevalence of internet use among adolescents in Varanasi, India. It shows that all adolescents had internet access as well as ownership of smartphone. It indicated a narrow digital access gap between male and female users. Despite similar levels of access, genders differ significantly in how they use the internet, significant gender difference was observed in platform preferences, privacy settings, and purposes of internet engagement. Gender played a major role in shaping online behaviours. Age and educational level further influenced patterns of digital engagement. In contrast, residential area did not significantly influence internet usage patterns, suggesting that digital behaviours are shaped more by individual and developmental factors than by geographic context. The study highlights the need for age and gender-specific digital literacy initiatives, school-based interventions, and parental guidance to promote responsible and balanced internet

DECLARATIONS

Research ethics statement(s): Informed consent of the participants was sought

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The author declares that they have thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Article

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Determinants, Knowledge and Constraints of Electronic National Agriculture Market (eNAM) Adoption in Tamil Nadu

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HIGHLIGHTS

- Education, social participation and digital literacy significantly influence farmers' participation in e-NAM.
- Knowledge levels are higher among e-NAM farmers and traders than non-e-NAM farmers.
- Phase-wise analysis shows higher knowledge in the payment and e-bidding stages of e-NAM.
- Financial, behavioural and infrastructural constraints limit e-NAM adoption among the stakeholders.

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ABSTRACT

The study aimed to analyse the factors influencing stakeholders' participation in the Electronic National Agriculture Market (e-NAM) using primary data collected from 390 respondents, comprising 150 e-NAM farmers, 150 non-e-NAM farmers, and 90 traders in Tiruvannamalai district of Tamil Nadu in 2025. A logistic regression model was used to identify the determinants of participation, while Garrett's ranking method was used to highlight the major constraints. The results revealed that social participation, education level, digital literacy and distance to markets are significant determinants of participation, whereas landholding, age, experience and income were found to be non-significant. Knowledge levels were higher among e-NAM farmers and traders compared to non-e-NAM farmers. Garrett's ranking technique revealed that immediate cash requirement, low digital literacy, technical difficulties, and poor market infrastructure were the major constraints of farmers, whereas traders highlighted competition among traders and non-uniform mandi policies as key challenges. The results suggest that awareness programmes, improved market infrastructure, standardised mandi practices and timely payments are essential to enhance e-NAM participation.

INTRODUCTION

Agriculture continues to play an important role in the Indian economy. It makes up 18% of GDP and employs about 45% of the workforce (Gupta et al., 2025). The traditional agricultural marketing system faces several inefficiencies, which create significant challenges. Farmers' price realization is greatly affected by issues like information asymmetry, fragmented markets, trader collusion, improper weighing practices, delayed payments and inadequate infrastructure (Swain et al., 2022; Patil et al., 2024). These structural inefficiencies not only reduce market function effectively, but also make it harder for farmers to make marketing decisions. Weak market linkages and inadequate institutional arrangements, such as the absence of farmer producer organisations (FPOs), limited cooperative support, poor credit access and insufficient extension services make farmers' income less stable and make them more vulnerable (Chand, 2016; Mohanraj et al., 2024). Small and marginal farmers are the most affected, because they often

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have to sell their crops right after harvest to pay off debts, which leads to distress sales and exposure to seasonal price changes.

Government of India launched the Electronic National Agriculture Market on 14 April 2016 as a nationwide online trading portal integrating Agricultural Produce Market Committees (APMCs). The platform is managed by the Small Farmers Agribusiness Consortium under the Ministry of Agriculture and Farmers Welfare to improve price transparency, reduce the role of intermediaries, and create a unified national agriculture market. As of June 2025, 1,522 mandis across 23 states and 4 Union Territories had been integrated into e-NAM, covering 247 commodities and registering approximately 1.83 crore stakeholders, of which farmers account for nearly 97.85% (e-NAM, 2025). Tamil Nadu stands out in terms of implementation with 213 integrated mandis and about 4.86 lakh registered stakeholders. However, the adoption and effective utilisation of e-NAM remain uneven across stakeholders. Previous studies have predominantly concentrated on farmers' awareness and perception, with limited attention on multi-stakeholder operational knowledge throughout transaction stages. Existing studies indicate that insufficient awareness and inadequate digital literacy are barriers to farmers' participation (Singh et al., 2021; Kumar et al., 2024). Weak market infrastructure and a lack of institutional support affect the platform's efficiency, especially for traders and intermediaries (Gautam et al., 2022).

Previous research has not adequately linked socio-economic characteristics with participation behaviour, nor have they examined functional knowledge across various phases of e-NAM transactions and compared users and non-users of e-NAM. This creates a critical gap in understanding the behavioural, informational and infrastructural constraints affecting adoption. It is hypothesised that socio-economic factors significantly influence farmers' participation, knowledge levels and adoption of e-NAM. To address these gaps, the present study aims to analyse the socio-economic determinants influencing farmers' participation in e-NAM, examine phase-wise functional knowledge among e-NAM farmers, non-e-NAM farmers and traders and assess the major constraints hindering adoption of the platform. The success of any policy initiative depends on the adoption behaviour and perception of its stakeholders (Badodiya et al., 2010). The findings of this study are expected to provide policy insights for improving the efficiency and inclusiveness of digital agricultural markets in India.

METHODOLOGY

The present study was conducted purposively in Tiruvannamalai District of Tamil Nadu due to its substantial agricultural arrivals and active participation in digital agricultural marketing through the e-NAM platform. The district comprises seven Agricultural Produce Market Committees (APMCs), of which Cheyyar and Chetpet mandis were selected based on their higher volume of online transactions and active stakeholder participation. The sampling frame was constructed using official records obtained from APMCs comprising 76 villages integrated into the market. The total population consisted of 1,200 farmers and 90 traders. The sample size was determined using Slovin's formula (Kabo-Bah & Bannor 2025).

$$N = \frac{N}{(1+N(e^2))}$$

Where, n = sample size, N = total population e = margin of error

For 5% margin of error, the required sample size was 300 farmers and 73 traders. A total of 390 respondents were selected to capture diverse stakeholder perspectives, including 150 e-NAM farmers, 150 non-e-NAM farmers and 90 traders. An explanatory research design was adopted to estimate the factors influencing the participation and adoption behaviour of respondents in e-NAM. Explanatory research designs were particularly useful in examining emerging phenomena such as digital agricultural platforms, where structured empirical evidence was evolving (Stebbins, 2001).

Primary data were collected during September and October, 2025 using a structured and pre-tested questionnaire. The 30-item knowledge assessment tool was validated by a panel of five subject-matter specialists for content validity and subsequently pre-tested with 20 farmers to ensure reliability and clarity of the instrument. The questionnaire covered socio-economic characteristics, functional knowledge across the e-NAM phases and challenges faced by stakeholders. Secondary data were collected from official reports, e-NAM database and APMCs records. Respondents were informed about the purpose of the study prior to data collection.

The binary logistic regression model was employed to estimate the determinants influencing participation in e-NAM, where the dependent variable was dichotomous and examined the probability of participation as influenced by independent variables (Raghavendra et al., 2023; Gautam et al., 2022). The logistic function was expressed as

$$\text{Logit}(P) = \ln\left(\frac{p}{(1-p)}\right) = \beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3\ldots\ldots\beta_nX_n$$

Where, β_0 = Intercept or constant term, β_1 to β_n = Coefficients representing the effect of independent variables on the likelihood of participation in e-NAM, $\left(\frac{p}{(1-p)}\right)$ = Odds ratio

The selection of explanatory variables was based on a comprehensive review of literature on agricultural technology adoption and e-NAM studies (Raju et al., 2022; Praneeth et al., 2023; Patil et al., 2024; Kumar et al., 2024). Distance to the market was included as an important factor, as earlier studies have shown it to be a key determinant of participation in e-NAM (Raghavendra et al., 2023). Additionally, a pilot survey was conducted among farmers in the study area, during which farmers themselves identified age, education, landholding size, farming experience, annual income, social participation, distance to market and digital literacy as the major factors influencing their participation in e-NAM. The variables were thus validated both empirically through literature and practically through direct farmer responses, ensuring contextual relevance and farmer-justified selection of determinants. Model fit was assessed using log-likelihood, Bayesian Information Criterion, Akaike Information Criterion and pseudo R^2 values.

Garrett's ranking analysis was used to rank the constraints faced by respondents in the adoption of e-NAM platform (Kumar et al., 2024). Each respondent was asked to rank the problems, and the per cent position was calculated as:

$$\text{Per cent Position} = \frac{100(R_{ij-0.5})}{N_j}$$

Where, R_{ij} = rank assigned by the jth respondent for the ith constraint, N_j = total number of constraints ranked by the jth respondent.

RESULTS

The socio-economic characteristics of the farmers indicate that farmers were predominantly middle-aged with considerable farming experience. The average landholding size was 3.57 acres, reflecting the dominance of small and marginal farmers in the study area. The respondents exhibited moderate levels of education and digital literacy, which influence their participation in digital agricultural marketing platforms. The findings indicate relatively low social participation among the respondents.

Factors influencing farmers' participation in e-NAM

The results of the binary logistic regression model (Table 1) revealed that education, social participation and digital literacy had a significant positive influence on participation in e-NAM ($p<0.05$), while distance to markets showed a significant negative effect ($p<0.001$). Age, landholding size, farming experience and annual income were found to be non-significant.

The model fit statistics (Table 2) confirmed that the model had good explanatory power, with McFadden Pseudo R^2 of 0.408 and Nagelkerke R^2 of 0.560, suggesting a satisfactory model fit.

Knowledge levels of respondents

The knowledge level of respondents (Table 3) on e-NAM was assessed using a structured set of 30 questions regarding the functioning of e-NAM. Each response was assigned a score of one, resulting in a maximum obtainable score of 30. The classification of respondents based on their knowledge levels was done using mean (14.41) and standard deviation (7.92). Although the standard deviation was relatively large, reflecting the heterogeneous knowledge levels across diverse stakeholder groups, the mean ± standard deviation classification method was retained as it is widely adopted in agricultural knowledge assessment studies (Raju et al., 2022; Praneeth et al., 2023). The findings indicated that knowledge levels varied considerably across different stakeholder groups. Among e-NAM farmers, a majority (52.66 per cent) possessed medium knowledge, while 42 per cent showed high knowledge levels. Traders showed relatively higher knowledge with 63.33 per cent in the medium category and 22.33 per cent had high levels of knowledge. Non-e-NAM farmers showed lower knowledge levels, with 62 per cent falling under low knowledge category.

Table 1. Logistic regression estimates for farmers' participation in e-NAM

Variables	Coefficient (β)	Odds Ratio	p-value
Age (X_1)	0.08	1.08	0.256^{ns}
Education(X_2)	1.26	3.51	0.029^{*}
Landholding size (X_3)	0.55	1.72	0.410^{ns}
Farming experience (X_4)	0.05	1.05	0.282^{ns}
Annual Income (X_5)	0.02	0.99	0.615^{ns}
Social Participation (X_6)	2.23	9.25	0.015^{**}
Distance (X_7)	-0.31	0.73	0.008^{**}
Digital Literacy (X_8)	2.98	19.61	0.014^{**}

ns = non-significant, * = 5% significance, ** = 1% significance

Table 3. Knowledge classification of respondents on e-NAM (%)

Knowledge Level	e-NAM farmers	Non-e-NAM farmers	Traders
Low (≤6.49)	5.33	62.00	13.33
Medium (6.49-22.23)	52.66	34.00	63.33
High (≥22.23)	42.00	4.00	23.33

Mean = 14.41; Standard Deviation = 7.92

Phase-wise functional knowledge of e-NAM

The phase-wise functional knowledge of respondents (Table 4) indicated that e-NAM farmers and traders exhibited moderate to high levels of knowledge across different phases of the e-NAM process, whereas non-e-NAM farmers showed comparatively lower levels of knowledge. For non-e-NAM farmers, the phase-wise knowledge assessment was based on their awareness and understanding of e-NAM procedures rather than actual participation in the platform. Among the various phases, the highest knowledge levels were observed in the payment phase, with 70 per cent among e-NAM farmers and 73.33 per cent among traders. This was followed by the e-bidding phase, where knowledge levels were 68.33 per cent among e-NAM farmers and 73.33 per cent among traders. Moderate knowledge levels were observed in the gate entry, sale agreement and gate exit phases for both e-NAM farmers and traders. Non-e-NAM farmers exhibited consistently lower knowledge levels across all phases, ranging from 23.33 per cent to 31.66 per cent. The lowest knowledge levels were observed in the sale agreement phase, followed by the assaying phase.

Table 4. Phase-wise knowledge of respondents in e-NAM (%)

Phases	e-NAM farmers	Non-e-NAM farmers	Traders
Gate Entry	54.66	26.00	49.33
Assaying	48.00	24.66	46.66
e-Bidding/Auction	68.33	30.00	73.33
Sale Agreement	54.44	23.33	58.88
Payment	70.00	31.66	73.33
Gate Exit	58.66	26.66	60.66

Values represented mean percentage knowledge scores across activities

Table 2. Model fit comparison

Model	Log-Likelihood	AIC	BIC	McFadden Pseudo R^2	NagelkerkeR^2
Model (intercepts only)	-37.45	-	-	-	-
Model (with predictors)	-22.16	68.32	93.45	0.408	0.560

Constraints faced by farmers and traders in e-NAM

The constraints faced by farmers and traders in e-NAM are presented in Figure 1 and 2. The results highlighted that financial, behavioural, technical and infrastructural factors influenced stakeholders' participation in e-NAM. The major constraint for the farmers was the need for immediate cash payments, followed by a strong preference for face-to-face selling and distrust in online transactions. Difficulties in repaying informal loans through digital platforms and issues related to e-NAM were identified as the major constraints. Infrastructural constraints such as inadequate grading facilities and lack of storage were relatively less identified challenges, while market-related constraints such as price reduction due to digital grading of the produce and longer auction duration were ranked lower.

For traders, higher competition from traders outside the region was identified as the major constraint, followed by non-uniform policies across mandis and limited infrastructural facilities, such as inadequate computers and a lack of technical staff. Technical issues, including system slowdown and difficulties in digital payment processes, were also reported. Difficulty in assessing quality without physical inspection was observed as an important constraint.

DISCUSSION

Education enhances the understanding of market dynamics and utilisation of digital platforms, while social participation facilitates information exchange and the collective decision-making process (Panda et al., 2019; Yadav et al., 2023). These findings support the diffusion of innovations theory, which emphasises the importance of communication channels and social systems in the technology adoption process. Digital literacy appears to be the most important factor, suggesting that familiarity with digital tools and platforms is essential for effective participation in e-NAM. Farmers with higher exposure to mobile applications, internet services and social media are equipped to access market information and complete online transactions. These findings are consistent with earlier studies, which reported that digital awareness significantly enhances the adoption of e-NAM (Klerkx & Rose, 2020; Raju et al., 2022; Niranjan et al., 2023; Praneeth et al., 2023; Patil et al., 2024; Godara et al., 2024; Kumar et al., 2024).

The negative influence of distance to market indicates that physical accessibility continues to affect participation in digital platforms. Farmers located farther from markets face higher transaction and information costs, which reduce their participation



Figure 1. Constraints faced by farmers in e-NAM

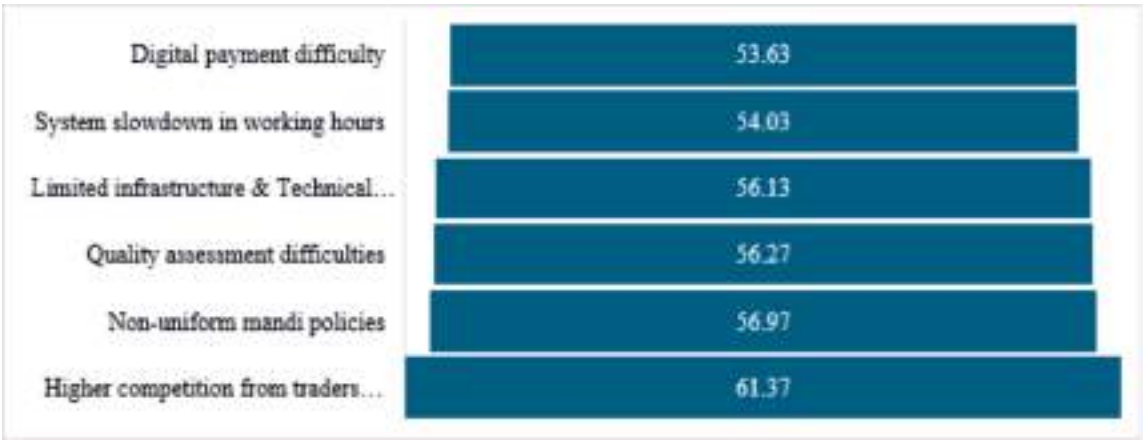


Figure 2. Constraints faced by traders in e-NAM

in digital platforms. This observation aligns with transaction cost theory and previous studies which explain that increased costs discourage participation in market activities (Fafchamps & Minten, 2012; Raghavendra et al., 2023).

The phase-wise knowledge of the e-NAM platform improves operational understanding across different transaction stages. Higher knowledge levels among e-NAM farmers and traders suggest that frequent interaction with the platform enhances familiarity with processes such as bidding and payment. Non-e-NAM farmers exhibit lower knowledge levels, indicating limited exposure and awareness. The comparatively higher knowledge in payment and e-bidding phases reflects the importance of these stages in actual transactions, while lower knowledge in assaying and gate exit procedures highlights gaps in technical understanding of the digital platforms. These findings are aligned with the results of Raju et al. (2022).

The financial, behavioural and infrastructural factors continue to limit the adoption of e-NAM. The need for immediate cash payments and preference for face-to-face selling indicate the persistence of traditional marketing practices and trust-based transactions. Distrust in online transactions and difficulties in loan repayment reflect behavioural and financial barriers. Technical challenges, such as difficulty in online processes and low digital literacy, reduce farmers' confidence in using digital platforms, while infrastructural limitations, such as inadequate grading facilities and a lack of storage facilities, affect the operational efficiency of the platform. These findings are consistent with Kumar et al. (2024); Nelson et al. (2025).

For traders, market-oriented and institutional constraints such as increased competition from outside traders and non-uniform mandi policies significantly influence participation. Technical challenges in digital platforms, including system slowdown and difficulties in digital payment processing, further hinder their engagement. These findings suggest that improving digital literacy, strengthening infrastructure, ensuring policy uniformity and building trust in digital transactions are essential for enhancing the effectiveness of e-NAM.

From an extension perspective, the identified constraints call for targeted interventions. Extension agencies should organise regular digital literacy training camps at the village level, focusing specifically on smartphone usage, online payment processes and e-NAM registration procedures. Establishing farmer help desks at mandis would assist in resolving technical difficulties during transactions. Facilitating linkages between farmers and formal credit institutions would address the immediate cash payment barrier effectively. For traders, harmonisation of mandi policies across APMCs and provision of adequate digital infrastructure, such as computers and reliable internet connectivity, are essential prerequisites. Capacity-building programmes involving both farmers and traders on a common platform would further foster mutual trust and improve the overall efficiency of the e-NAM platform.

CONCLUSION

The study highlights that socio-economic factors significantly influence farmers' participation in e-NAM. Education, social participation and digital literacy enhance adoption, while distance to markets continues to limit participation. Higher knowledge levels among e-NAM users indicate that digital platforms improve operational understanding across transaction stages. Financial dependence on immediate cash, preference for traditional marketing practices and the infrastructural limitations restrict effective adoption. The findings highlight that strengthening digital literacy, improving market infrastructure, and ensuring policy uniformity are essential for enhancing participation in e-NAM. The study emphasises the importance of behavioural and institutional factors in digital agricultural marketing and suggests that targeted extension interventions and capacity building efforts are necessary to improve the efficiency and inclusiveness of e-NAM.

DECLARATIONS

Ethical approval and consent to participate: Informed consent was obtained from all respondents prior to data collection.

Competing interests: The authors declare that they have no competing interests.

Conflict of interest: The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have critically reviewed, revised, and approved the manuscript and take full responsibility for its content.

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Research Article

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Socio-economic Determinants of Environmental Risk and Safe Pesticide Use: A Canonical Correlation Analysis

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HIGHLIGHTS

- Growers' perceptions and socio-economic factors were found to be strongly correlated by canonical correlation analysis.
- The first canonical function, which was dominated by attitude, knowledge, education and the perception of safe pesticide usage, explained 81.72% of the shared variance.
- Attitude and knowledge emerged as key predictors shaping growers' perceptions of pesticide safety and environmental risk.
- Second canonical function showed moderate association, highlighting area under chilli crop and environmental risk perception.

ARTICLE INFO

Keywords: Chilli growers, Canonical correlation analysis, Environmental risk perception, Safe pesticide use, Socio-economic characteristics.

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ABSTRACT

The study was conducted in 2025-26 at Guntur District of Andhra Pradesh and examines the significant impact on socio-economic factors of chilli growers and their perceptions of environmental risk and safe pesticide use in the study area. Canonical correlation analysis (CCA) was used to identify the connection between independent variables with dependent variables of chilli growers. A multistage sampling technique was used to choose 160 chilli growers from four mandals in the Guntur district. Perceptions of environmental risk and safe pesticide use were regarded as dependent variables, while eleven socioeconomic factors were classified as independent variables. The first canonical pair of variates showed stronger canonical correlation of 81.72 per cent with high Eigen values. It was mainly influenced by attitude, knowledge, education, age and information source. The second function, showed 37.58 per cent of the shared variance was mostly determined by structural characteristics that influenced perceptions of environmental risk, specifically the area under chilli cultivation. The findings suggest how cognitive, attitudinal and resource-based socioeconomic factors significantly influence growers' perspectives. Promoting ecologically safe pesticide practices requires bolstering extension interventions that emphasize knowledge, attitude and risk communication.

INTRODUCTION

Chilli (*Capsicum annuum*) belongs to the Solanaceae family. It is an important horticultural crop with commercial and nutritional importance (Delai et al., 2024; Goddu et al., 2025). In 2023, there were 18.03 lakh hectares of chilli cultivation worldwide, with an average productivity of 3,229 kg per hectare and a production of 58.22 lakh tonnes. India is the world's largest producer, consumer, and exporter of chillies, followed by China, Thailand, Ethiopia, and Indonesia (Daravath et al., 2025). In 2023–2024, 8.09 lakh hectares of chilli cultivation were grown in India, with an average productivity of 3273 kg/ha and an expected production of 29.13

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lakh tonnes. 33% of the nation's total spice exports are chillies alone (Singh et al., 2024). Andhra Pradesh tops the states in chilli production with 14.44 lakh tons (49.57%), grown on 2.47 lakh hectares (27.75%) with a productivity of 5846 kg/ha, followed by Telangana, Madhya Pradesh, Karnataka and West Bengal (Janaki et al., 2023). Guntur is the most productive district for chilli farming, with a yield of 8354 kg/ha, grown on 19,000 hectares, producing 159,000 tonnes (Centre for Agriculture and Rural Development Policy Research, 2023). The state of Andhra Pradesh as a whole contributes 40% of India's chilli production, while Guntur alone contributes 15% of the total (One District One Product, 2024). Guntur exports Rs. 100 crore worth of chillies annually to the United States, the United Kingdom, Japan, France, Sri Lanka, and other countries (Kumari & Nahatkar, 2021). Despite having significant export potential, the chilli crop is severely impacted by a wide range of pests and viral diseases (Prabhavathi et al., 2025). However, thrips (*Scirtothrips dorsalis*) is a common pest of chillies and is present throughout the growing season. The incidence of flower thrips (*Thrips parvispinus*) has been documented for the first time in India's chilli ecosystem (Sireesha et al., 2021). Despite its economic significance, Guntur's chilli faces intense pest pressure, forcing many growers to rely heavily on chemical pesticides. This led to pesticide-residue issues that harmed export shipments and raised concerns about environmental risks and human health (Sharma et al., 2020; Sahar et al., 2020). Over half of the world's pesticides are used in Asia, with India ranking third in Asia after China and Turkey and 12th overall (Yadav, 2024; Das et al., 2025). Andhra Pradesh accounts for 22.5% of the nation's pesticide use (Prabhavathi et al., 2020). Guntur District spends Rs. 450–500 crore a year, mostly on cotton and chilli cultivation, making it the district with the highest pesticide use. Previous research on farmers' perceptions of environmental risk and pesticide use has mostly relied on univariate or bivariate methods. Furthermore, there is limited combined evidence particularly from pesticide-intensive chilli-growing regions like Guntur district because environmental risk perception and safe pesticide usage are frequently examined independently. To fill the gap, the study uses Canonical Correlation Analysis to concurrently analyze eleven socioeconomic variables and two perceptual dimensions, providing an integrated understanding and supporting data for targeted extension initiatives and policy creation.

METHODOLOGY

The study was carried out in Guntur District, Andhra Pradesh, due to its dominance in chilli cultivation and high pesticide use intensity. The respondents were chosen using a multistage sampling process. In the initial stage, four mandals were purposively chosen based on the extreme availability of chilli cultivation. At the second stage, two villages were randomly selected from each mandal, for a total of eight villages. In the final stage, 20 chilli farmers were randomly selected from each village, yielding a sample of 160 respondents. A pre-tested, well-structured interview schedule was used to gather data from the respondents. While knowledge was evaluated using objective items scored dichotomously (correct = 1, incorrect = 0), attitudes toward safe pesticide use and perceptions of environmental risk and safe pesticide usage were measured using five-point Likert-type scales, with responses ranging from strongly disagree (1) to strongly agree (5). The data were analysed in SPSS and R-Studio software using Pearson's correlation, Multiple Linear Regression and Canonical Correlation Analysis to investigate the relationships between the independent variables and both perceptions of chilli growers. Variance Inflation Factor (VIF) was used to assess multicollinearity between the independent variables before Canonical Correlation Analysis. Even while some socioeconomic factors had higher VIF values, these factors were conceptually different and logically pertinent to research on farmers' perceptions.

In this work, a multivariate analysis was performed using Canonical Correlation Analysis (CCA), a well-known technique for identifying the correlations between two sets of variables X and Y (Sahoo et al., 2024). The linear function of one set of variables that is closely related to that of another can be identified using CCA (Akour et al., 2023).

Two sets of variables were considered in the study: eleven independent variables (X) representing socioeconomic factors and two dependent variables (Y).

$$X = x1, x2, x3,\ldots\ldots x11 \text{ and } Y = y1, y2$$

Where, x1 = age, x2 = education, x3 = experience , x4 = l and holding, x5 = area under chilli cultivation, x6 = income, x7 = source of information, x8 = risk orientation, x9 = economic motivation and x10 = knowledge, x11 = attitude, y1 = perception towards environmental risk, y2 = Perception towards safe usage of pesticides.

Since the number of canonical correlation pairs is equal to the number of characters in the smallest set, two canonical correlation pairs U_1, V_1, and U_2, V_2 were evaluated in the present study.

RESULTS

The correlation coefficient analysis of Table 1 reveals that education, knowledge, attitude, source of information and land holding showed highly significant at 0.001% level, while age exhibited negative significance with perception towards environmental risk and perception towards safe usage of pesticides.

Table 1. Correlation co-efficient (r) of independent variables and dependent variables

Variables	Pearson Correlation	
	Perception towards environmental risk	Perception towards safe usage of pesticides
Age	-.525**	-.680**
Education	.694**	.727**
Experience	-0.030	-0.023
Land holding	0.144	.364**
Area under chilli crop	-0.022	.326**
Income	0.068	.261**
SOI	.422**	.537**
RO	.245**	.178*
EM	.303**	.170*
Knowledge	.654**	.754**
Attitude	.658**	.818**

*Significant at 5%; ** Significant at 1%

Table 2. Multiple Linear Regression analysis of independent variables with both dependent variables

Variables	Perception towards environmental risk (R^2 =0.788)					Perception towards safe usage of pesticides (R2 =0.615)					
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics
	B	Std. Error	Beta			B	Std. Error	Beta			VIF
Age	-4.678	5.308	-0.105	-0.881	0.38	3.764	1.8	0.334	2.091	0.038	9.846
Education	-10.395	2.504	-0.658	-4.152	0	3.571	0.849	0.898	4.206	0	17.526
Experience	-2.924	1.544	-0.084	-1.894	0.06	-0.621	0.524	-0.071	-1.187	0.237	1.380
Land holding	6.641	2.562	0.297	2.592	0.01	-0.543	0.869	-0.097	-0.625	0.533	9.194
Area under chilli crop	4.227	1.413	0.171	2.992	0.003	-1.247	0.479	-0.2	-2.603	0.01	2.283
Income	-5.827	3.177	-0.203	-1.834	0.069	2.058	1.077	0.284	1.91	0.058	8.531
SOI	-1.396	0.816	-0.136	-1.711	0.089	-0.351	0.277	-0.136	-1.268	0.207	4.399
RO	0.278	0.366	0.034	0.758	0.449	0.323	0.124	0.156	2.602	0.01	1.384
EM	-0.483	0.961	-0.024	-0.503	0.616	1.012	0.326	0.196	3.108	0.002	1.532
Knowledge	1.729	0.74	0.381	2.335	0.021	0.332	0.251	0.291	1.324	0.187	18.593
Attitude	2.982	0.323	1.059	9.231	0	-0.08	0.11	-0.113	-0.729	0.467	9.187

The regression analysis Table 2 of perception towards environmental risk accounted for 78.8 per cent of the variation among chilli growers. Attitude ($\beta = 1.059$, $p < 0.01$) and knowledge ($\beta = 0.381$, $p < 0.05$) showed positive significance, while education ($\beta = -0.658$, $p < 0.01$) showed negative significance. The dependent variable, perception of safe pesticide use, showed that 61.5 per cent of the variation occurred among chilli growers. Education ($\beta = 0.898$, $p < 0.01$) and age ($\beta = 0.334$, $p < 0.05$) showed positive, significant relationships, while area under chilli crop ($\beta = -0.200$, $p < 0.05$) showed a negative significant relationship. The Variance Inflation Factor (VIF) shows that several independent variables exhibit multicollinearity. Knowledge (VIF = 18.593) and education (VIF = 17.526) exhibit severe multicollinearity, beyond the critical threshold of 10. Strong interrelationships are suggested by the high but acceptable multicollinearity of age (9.846), landholding (9.194), attitude (9.187), and income (8.531). On the other hand, low multicollinearity (VIF < 5) indicates steady and independent contributions to the model for experience, area under chilli crop, source of information (SOI), risk orientation (RO), and economic motivation (EM).

The statistical canonical correlation analysis displayed in Table 3 indicates that both canonical functions were statistically significant at the 0.00 level. With a low Wilks' statistic (0.114), the first canonical pair, U_1 and V_1, showed a very strong canonical correlation (0.904) with a high eigenvalue (4.479), explaining 81.72% of the shared variance between socioeconomic characteristics and growers' perceptions of environmental risk and safe pesticide use. Despite having a higher Wilks' statistic (0.625), the second canonical pair, U_2 and V_2, likewise had a significant but somewhat mild connection (0.613) with an eigenvalue of 0.601, accounting for 37.58% of the shared variance.

From Table 4, canonical loadings indicate that attitude (-0.948), knowledge (-0.890), education (-0.879), age (0.780) and source of information (-0.619) all had stronger correlations with U1 in the first canonical function U_1 and V_1, whereas perception of the safe use of pesticides (-0.966) had a strong correlation with V_1. In the second canonical function, U_2 and V_2, Area under chilli crop (0.506) had a comparatively larger association with U_2, whereas perception of environmental risk (-0.676) had the strongest correlation with V_2.

Table 4. Canonical loadings and cross-loadings analysis of socio-economic characteristics with different perceptions of growers

Independent variables	Canonical loadings		Canonical cross-loading	
	U_1	U_2	U_1	U_2
Age	.780	.013	.706	.008
Education	-.879	-.260	-.795	-.159
Experience	.030	.025	.027	.015
Landholding	-.371	.250	-.336	.153
Area under chilli crop	-.281	.506	-.254	.310
Income	-.255	.244	-.230	.150
SOI	-.619	-.023	-.559	-.014
RO	-.241	-.205	-.218	-.125
EM	-.253	-.324	-.229	-.198
Knowledge	-.890	-.147	-.805	-.090
Attitude	-.948	-.065	-.857	-.040
Dependent Variables	V1	V2	V1	V2
perception towards environmental risk	-.737	-.676	-.666	-.414
Perception towards safe usage of pesticides	-.966	.258	-.874	.158

Table 3. Canonical correlation analysis of socio-economic characteristics and different perceptions of growers

Pair of canonical	Canonical correlation	Square of canonical correlation	Eigenvalue	Wilks Statistic	Probability
U_1 V_1	0.904	0.817216	4.479	0.114	<0.000
U_2 V_2	0.613	0.375769	0.601	0.625	<0.000

In the canonical cross-loading analysis, it was shown that attitude (-0.857), knowledge (-0.805), education (-0.795) and age (0.706) had stronger cross-loadings with U_1 in the first canonical function U_1 and V_1, showing their substantial association with the dependent canonical variate. Perception of the safe use of pesticides (-0.874) showed high cross-loadings with V_1 among the dependent variables. Cross-loadings were very modest in the second canonical function, U_2 and V_2, which showed an area under chilli crop (0.310), indicating a moderate correlation with U_2. However, perception of environmental risk (-0.414) had the largest cross-loading among dependent variables with V_2.

Table 5. Standardised and unstandardised canonical coefficients analysis of socio-economic characteristics and different perceptions of growers

Independent variables	Standardised Canonical Correlation Coefficients		Unstandardised Canonical Correlation Coefficients	
	U_1	U_2	U_1	U_2
Age	-.020	-.775	-.041	-1.572
Education	.280	-2.617	.201	-1.878
Experience	.099	.013	.156	.020
Landholding	-.231	.605	-.234	.613
Area under chilli crop	-.084	.619	-.094	.694
Income	.084	-.821	.109	-1.071
SOI	.166	.060	.078	.028
RO	-.083	-.244	-.031	-.091
EM	-.045	-.400	-.042	-.373
Knowledge	-.436	-.001	-.090	.000
Attitude	-.901	1.721	-.115	.220
Dependent Variables	V1	V2	V1	V2
perception towards environmental risk	-.306	-1.146	-.055	-.207
Perception towards safe usage of pesticides	-.802	.874	-.036	.040

From Table 5, standardised canonical coefficients, attitude (-0.901) had a stronger correlation with U_1 among independent variables in the first canonical function U_1 and V_1, although perception of safe pesticide usage (-0.802) dominated the dependent side with V_1. Education (-2.617) and attitude (1.721) had a greater correlation among independent factors with U_2 in the second canonical function U_2 and V_2. Perception of environmental risk (-1.146) had the greatest correlation with V_2 among the dependent variables.

In unstandardized canonical correlation coefficients, land holding (-0.234) and education (0.201) had comparatively greater correlations with U1 among independent factors, from the first canonical function U_1 and V_1. Perception of environmental danger (-0.055) contributed slightly more to the dependent variable (V_1) than perception of safe pesticide use (-0.036). Education (-1.878) and age (-1.572) had a better association with U_2 in the second canonical function U_2 and V_2, whereas perception of environmental risk (-0.207) demonstrated a stronger correlation with V_2 among dependent factors.

DISCUSSION

The correlation showed that education, knowledge, attitude, and source of information were positively associated with both perceptions, while age was negatively associated with perceptions of environmental risk. It shows that younger, educated farmers take environmental issues more seriously. The multiple regression analysis shows that, while age, education, economic motive, and risk orientation encourage safer pesticide use, attitude, knowledge, and risk awareness significantly affect farmers' perceptions of environmental risk (Sahar et al., 2020). It suggests that experienced, knowledgeable, and financially motivated farmers implement safe methods to reduce environmental risk and use pesticides safely. According to the multicollinearity pattern, farmers' perceptions of pesticides are influenced by an interconnected socio-cognitive cluster that includes education, knowledge, attitude, age, income and landholding. The canonical correlation analysis revealed a high association between the socioeconomic characteristics of chilli growers and their perceptions of environmental risk and safe pesticide use. The presence of two statistically significant canonical functions indicates that growers' perceptions are influenced by several underlying socioeconomic factors. With a low Wilks' Lambda value and a very high canonical correlation (0.904), the first canonical function (U_1V_1) accounted for 81 per cent of the shared variance. This implies a strong, consistent primary link between socioeconomic determinants and perception variables. According to canonical loadings, the most significant factors influencing U_1 were attitude, knowledge, education, age and source of information (Pujitha et al., 2024). Growers with more positive attitudes and higher levels of knowledge tend to have stronger perceptions of safe pesticide use, as indicated by the strong negative loadings of attitude and knowledge (Uikey et al., 2025). Another important factor that surfaced was education, emphasising how formal education shapes awareness and appropriate pesticide use (Paine et al., 2021). Age showed a positive loading, indicating that older farmers may have more life experience, which influences their perception of pesticide safety (Nurika et al., 2022). Perception of safe pesticide use on the dependent side with V_1 showed very high loadings and cross-loadings in the first canonical function, indicating that growers' cognitive and attitudinal characteristics account for the majority of this perception dimension (Afandi & Irfan, 2024).

Strong cross-loadings further confirm that these socioeconomic indicators do not reflect misleading associations but rather are substantially linked to views of safer pesticide use. The second canonical function (U_2V_2) only accounted for 37% of the shared variance. Area under chilli crop emerged as the most influential independent variable, indicating that the farm size devoted to chilli cultivation plays an important role in shaping growers' perceptions in this dimension. Farmers may be more sensitive to environmental risks if a larger area is planted with chilli crops, as this could increase production risks and pesticide use (Nehul, 2025). The dependent side of the second function, where perception of environmental risk showed the highest loadings and cross-loadings, lends credence to this argument. By identifying variables that specifically contributed to each canonical variate after adjusting for intercorrelations,

standardised canonical coefficients further improved interpretation. The first function was dominated by attitude, highlighting its crucial role in shaping opinions about the safe use of pesticides. Education and attitude demonstrated significant but conflicting standardised effects in the second function, indicating a more intricate relationship between behavioural orientation and cognitive awareness regarding environmental risk perception (Vandenberg et al., 2025). The unstandardized coefficients highlighted the importance of economic ability and farming experience in shaping perception patterns, showing that landholding, age and education had significant practical impacts. The findings show that U, is largely defined by farm structural characteristics influencing V_2, which represents perceptions of environmental risk, while U_2 is primarily defined by cognitive and attitudinal socio-economic variables influencing V_1, which represents perceptions of safe pesticide use.

CONCLUSION

The most important variables affecting farmers' perceptions of environmental risk and safe pesticide use are attitude, knowledge, education, and source of information. The canonical correlation analysis indicates that socio-economic characteristics are significantly related to chilli growers' perceptions of environmental risk and safe pesticide use. The first canonical pair (U_1V_1) was strongly significant in influencing growers' perceptions with attitude, knowledge, education, age and source of information. This suggests that cognitive and attitudinal factors play a key role in promoting safer pesticide practices. The second pair (U_2V_2) revealed that socioeconomic factors were strongly associated with perception towards environmental risk, indicating that larger-scale growers are more sensitive to environmental hazards. The study recommends that extension and policy interventions be differentiated and CCA-guided, with a primary focus on growers' knowledge and attitudes through education and information-based approaches to improve safe pesticide use.

DECLARATIONS

Ethical approval and informed consent: No ethical approval is needed for this study, however, the informed consent was sought from participants.

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Research Article

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Enhancing Extensionists' Capabilities in Female Farmers' Groups (FFGs) Empowerment: An Integrative Approach

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HIGHLIGHTS

- Integrated training enhanced extension workers' participatory, pluralistic, and entrepreneurial facilitation competencies
- Business Model Canvas improved goal-setting and business planning among female farmer groups
- Gender-sensitive extension practices increased, though greater analytical and transformative skills remain limited
- Pluralistic approaches strengthened cross-sector collaboration in supporting female farmer groups.

ARTICLE INFO

Keywords: Business model canvas, Extension capability, Female-led farmer groups, Gender-sensitive extension, Participatory, Pluralistic extension.

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ABSTRACT

Strengthening extensionists' skills is crucial for advancing agricultural development. The research aims to assess the extension workers' capacity following online training on integrated extension approaches. The research was conducted from February 2024 to February 2025 in Bogor, Karawang, Subang, and Purwakarta Regencies, West Java, Indonesia, involving 51 extension workers as the primary research participants and supporting 153 farmer groups comprising 3,825 farmers. The extension workers participated in the training focused on supporting female farmer groups. A competency gap analysis highlighted the need for online training modules to enhance extensionists' skills in non-production-related topics. The modules covered four areas, including participatory extension, pluralistic extension, gender-sensitive extension, and the Business Model Canvas. The modules aimed to improve facilitation and entrepreneurial skills. Reflective assessments and field mentoring showed that extensionists enhanced their capabilities in participatory and pluralistic approaches. However, challenges remain in implementing gender-sensitive extension, as many still struggle to identify gender disparities in economic activities and decision-making roles. These results suggest that while integrated training improves professional and technical skills, larger institutional and cultural changes are needed to fully incorporate gender sensitivity into extension. The program emphasizes the importance of continuous participatory learning, gender, and business approaches for inclusive agricultural progress.

INTRODUCTION

Agricultural extension education strengthens female farmer groups (FFGs) through group-based approaches recognized for women's empowerment (Sen et al., 2025). It fosters technological transformation, organizational capacity, reduces post-harvest losses (McNamara & Tata, 2015), and boosts entrepreneurship (Amanah

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& Fatchiya, 2018; Nyathi & Even, 2022; Yaseen et al., 2024). In addition to technical expertise, extension workers need soft skills, communication, and facilitation skills (Shivamuthry & Madhushree, 2023). Resource constraints and wide service areas limit the use of face-to-face methods, making online training a promising, scalable, and sustainable alternative to enhance extension capacity and facilitate inclusive engagement (Gentry et al., 2017; Estefan et al., 2025).

Women's empowerment in agriculture has attracted growing attention. Despite this, women continue to face barriers to extension services, technologies, financial resources, and decision-making (Nain & Kumar, 2010; Quisumbing et al., 2023). Evidence shows that equal access to these resources can significantly improve agricultural productivity (Diaz & Najjar, 2019). However, in many countries, extension systems remain primarily targeted at male farmers. In contrast, participatory, pluralistic extension models better promote women's inclusion (Singh et al., 2014). In Indonesia, decentralization reform efforts still focus on production, with limited gender-responsive facilitation (Indriyani et al., 2024; Dewi et al., 2025). Various initiatives have aimed to enhance women's participation in agriculture, including sustainable food yards and small-scale agribusiness to improve nutrition and income. However, these interventions are frequently project-based, which constrains their sustainability and long-term impact on FFG capacity development (Begum, 2025). Furthermore, numerous programs do not adequately reach female farmers, thereby impeding technology adoption and limiting market access (Curtin et al., 2024). Expanding women's access to training, information, and extension services has been shown to enhance their decision-making authority, access to resources, and participation in farmer groups (Siaw et al., 2024), underscoring the importance of ongoing extension support.

Integrating entrepreneurial concepts into agricultural extension is vital for transforming farming and fostering inclusive agribusiness. The Business Model Canvas (BMC), a strategic tool for entrepreneurs, is increasingly used as a gender-responsive support tool. Many FFGs still face challenges such as limited capacity for inclusive extension, restricted access to capital and markets, and cultural norms that limit women's decision-making, all of which are amplified by resource inequalities (FAO, 2023; Arintyas, 2024).

Given these conditions, strengthening extension workers' capacity through integrated approaches is critical and essential for more sustainable impact on FFGs. Although previous studies have examined participatory, gender-sensitive, and agribusiness-oriented extension separately, integrated frameworks combining these dimensions remain limited. The research addresses this gap by adopting an Integrated Extension Approach (IEA) incorporating participatory, pluralistic, gender-sensitive, and entrepreneurial elements, including the BMC. It aims to evaluate the effectiveness of integrative online training for extension workers and to examine the challenges of implementing such approaches to empower FFGs.

METHODOLOGY

The research was conducted from February 2024 to February 2025 in Bogor, Karawang, Subang, and Purwakarta Regencies, West Java Province, Indonesia, with a focus on their strong agricultural activity, active FFGs, and extension worker capacity. Involving 51 purposively selected extension workers supporting 153 farmer groups with 3,825 farmers, it used a mixed-methods, quasi-experimental design with monthly surveys. A one-group quasi-experimental approach (McLeod-Morin et al., 2023; Capili & Anastasi, 2024), evaluated the extent to which extension workers improved skills to support FFGs. This design was chosen because all 51 workers participated, making the use of control groups impractical. This design suited the limited resources and participant availability.

The training curriculum was designed to enhance extension workers' skills through four materials: participatory, pluralistic, gender-sensitive, and the BMC tool. Data were gathered via pre and post-tests. A rapid rural appraisal (RRA) in June 2024 assessed the extension competency gap (pre-tests) on the integrative extension approach. An online training in July 2024 used a quasi-experimental design to evaluate how extension workers improved their knowledge and skills in the integrative approach.

After training, monthly surveys were conducted to assess the extent to which the extension workers used integrated approaches. Three post-tests were administered from July to August 2024 to measure changes in competency. In September, field visits to eight female farmer groups (FFGs), chosen for extension workers' practical use of at least two training modules, were observed. A final evaluation in November 2024 summarized results.

Both quantitative and qualitative analyses examined learning experiences, challenges in applying gender-sensitive approaches, and the use of participatory methods and the BMC to support female farmer groups. Descriptive statistics (Neuman, 2014) summarized numerical data. Changes in extension workers' competencies were assessed through training implementation, observed changes, and the post-training performance of 51 workers who completed the online training. Qualitative data were collected through field observations, interviews, group discussions, and reflective dialogues with extension workers.

A Context, Input, Process, and Product (CIPP) evaluation model (Stufflebeam & Zhang, 2017) was used to assess extension workers' capabilities. Context evaluation identified needs, problems, and opportunities for the training program. Input evaluation examined resources, strategies, and design, including the curriculum, materials, methods, facilitators, technical assistants, and digital infrastructure. Process evaluation assessed delivery, engagement, and interactions during the training. Product evaluation measured outcomes, focusing on changes in extension workers' capability.

RESULTS

CIPP evaluation of the integrated extension training program

Figure 1 summarizes the evaluation findings. The CIPP model evaluation shows that improvements in extension workers' competencies were significant in applying participatory approaches, facilitating gender-sensitive discussions (82.4%), facilitating goal-setting (92.2%), using the BMC (74.5%), and cross-sector collaboration (54.9%). These findings indicate that the training program strengthened extension workers' capability.

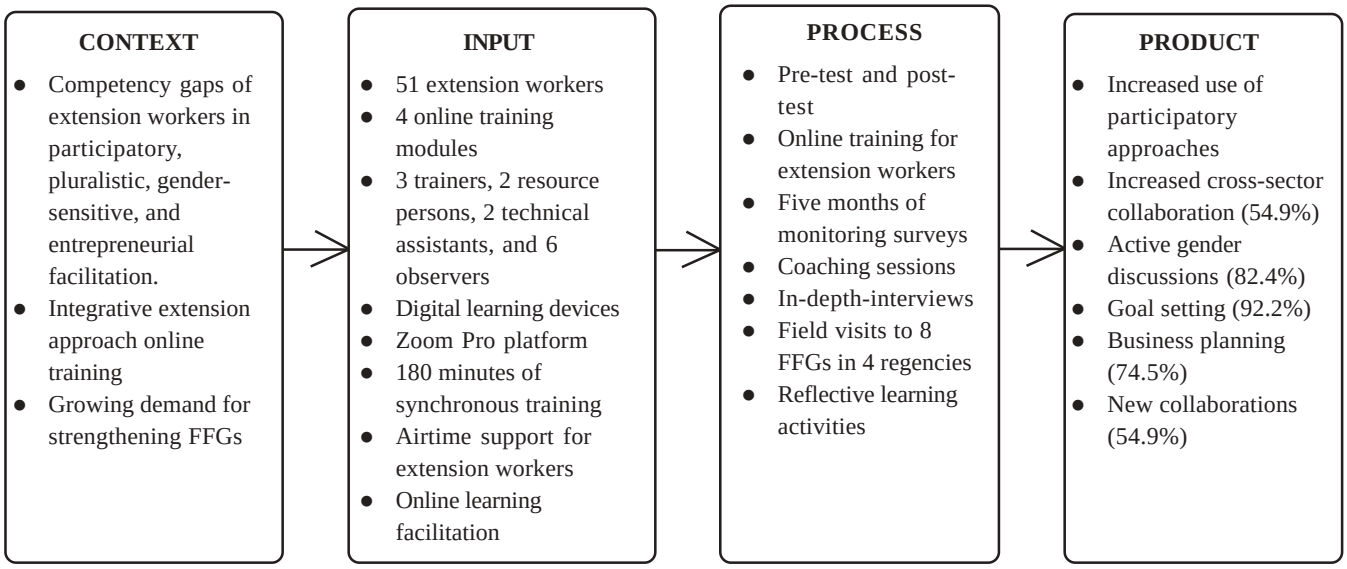


Figure 1. Results of the CIPP evaluation of the integrated extension training program for extension workers

Context

Agricultural extension in Indonesia began in the early 19th century, with a focus on food security. Extension workers have planned programs to boost food-crop production using the T&V approach since the 1980s; these programs have been modified but still lack gender sensitivity, entrepreneurship, and BMC model development. The COVID-19 pandemic prompted Indonesia to develop an Extension Information System that connects extension workers nationwide with virtual training, training one million farmers and workers monthly. However, training primarily focuses on productivity, neglecting needs assessment, strategic planning, and organizational management. Farmer training often emphasizes individual rather than group efforts. Indonesia has about 60,000 farmer groups, mostly in villages, with FFGs more engaged in food processing and selling diverse products to markets, requiring different extension support. A preliminary assessment using RRA found that extension services remained largely production-oriented, while participatory facilitation, gender-sensitive analysis, pluralistic collaboration, and entrepreneurial development received limited attention. The training was implemented as a collaborative effort among IPB University, the University of Illinois Urbana-Champaign, and partners in Indonesia's agricultural extension system. The program aimed to strengthen extension workers' capacity to facilitate the formation of inclusive groups and to support income-generating activities among FFGs.

Input evaluation

A training program was developed to address competency gaps among agricultural extension workers supporting female farmer groups in four West Java Regencies: Bogor, Karawang, Subang, and Purwakarta. These areas have diverse agricultural contexts and varying extension capacities. The program involved 51 extension workers in an online course on integrated extension, including stakeholders from the Ministry of Agriculture, IPB University, the private sector, and training assistants. These workers supported 153 farmer groups with about 3,825 farmers, providing real-world training applications. The curriculum covered four modules: participatory, pluralistic, gender-sensitive extension, and BMC for agribusiness planning, aimed at enhancing facilitation skills, multi-stakeholder collaboration, and entrepreneurship among female farmers. Delivered via an online platform with airtime and internet access, the training included digital modules, facilitation tools, and interactive activities such as discussions and group work to promote engagement and field application.

Process evaluation

The training program included online sessions, discussions, and practical exercises to simulate real-world extension facilitation. Participants were divided into small groups to develop strategies integrating participatory approaches, gender perspectives, and business planning for FFGs. Afterward, extension workers applied these materials to support FFGs. Monitoring through surveys, coaching, interviews, and field visits assessed how extension workers implemented the materials and how FFGs responded. Data showed a steady increase in the use of training materials, with 94.1% of extension workers facilitating discussions with female groups by November 2024. Participation in needs assessments ranged from 82.6% to 92.2%. Discussions on gender issues increased, with those discussing gender differences rising from 52.2% in August to 82.4% in November 2024.

Product evaluation

The evaluation showed improvements in extension workers' skills and facilitation practices after training. Table 1 compares baseline and post-training performance across key competencies, revealing gains in all areas. Participatory facilitation shifted from directive to interactive, group-based learning. Pluralistic skills expanded from a public-sector focus to broader engagement. Gender awareness moved from conceptual understanding to active discussions on the gender gap. BMC facilitation skills, once rare,

Table 1. Competency change and remaining gaps among extension workers

Competency dimension	Baseline condition (before the training)	Post-training performance	Direction of change
Participatory facilitation	Mostly top-down approaches	Widely practiced in group facilitation	High improvement
Pluralistic extension	Primarily public-sector oriented	Increased cross- sector discussions, still limited cross-sector collaboration	Moderate-high improvement
Gender-sensitive analysis	Conceptual awareness, limited practice	Active discussions about gender gaps, but limited discussion on gender-sensitive analysis	Moderate improvement
BMC facilitation skills	Never to rarely practiced	Frequently practised with FFGs	High improvement

became common in supporting FFGs. Most extension workers facilitated goal setting (92.2%), new business discussions (80.4%), and helped start new activities (74.5%) and develop business plans (74.5%) during post-training evaluation.

Pluralistic extension skills improved as practices shifted from a public-sector focus to collaboration with the private sector, civil society, and universities. Of 51 trainees, 25 partnered with these sectors for the FFG program, including *Subang* with a seed company and *Karawang* with *Pertamina*, a state-owned enterprise in Indonesia. Most progressed from conceptual awareness of gender to active discussions of gender gaps in extension. BMC facilitation skills advanced from rarely used to frequently apply with female farmer groups. Overall, competency improvements ranged from moderate to substantial, with the highest gains in participatory facilitation, BMC, pluralistic extension, and gender-sensitive analysis.

Change in extension workers' competency after the training

Table 2 shows changes in extension workers' competencies across knowledge, attitudes, and skills from baseline to post-training. Initially, gender was viewed primarily in terms of women's participation, with few open discussions. After training, 82.4% discussed gender-based work-time gaps, and 100% focused on access to and control over resources.

Practical skills improved notably. Initially, the BMC was rarely used; post-training, 92.2% facilitated goal-setting with FFGs. Additionally, 74.5% helped develop business plans, and 80.4% discussed new business ideas. Facilitation shifted from directive to interactive, with 92.2% of group discussions led. Regarding cross-sector work, early conditions showed limited collaboration. After training, 54.9% reported working with other sectors, and 66.7% engaged in cross-sector discussions.

Figure 2 shows agricultural extension workers' (N=51) mostly positive perceptions of training. For the statement, "This training met my expectations," 68.63% agreed, 27.45% strongly agreed, 3.92% strongly disagreed, and none disagreed.

Extension workers across all dimensions mostly reported positive perceptions. Most extension workers chose "agree" or "strongly agree" for all statements, with only a small percentage selecting "neutral" or "disagree." Concerning understanding, 74.51% agreed, and 17.65% strongly agreed that the training material was clear, while only 5.88% were neutral and 1.96% strongly disagreed. A similar trend appeared for ease of use: 76.47% agreed, and 19.61% strongly agreed that the material was easy to follow, with minimal neutral and strongly disagree responses at 1.96% each.

Regarding readiness to apply the training, 78.43% of respondents agreed, and 15.69% strongly agreed that sufficient knowledge was gathered, while only 1.96% were neutral and 3.92% strongly disagreed. A comparable distribution was observed for perceived relevance: 76.47% agreed, and 17.65% strongly agreed that the training content was relevant to the needs of female farmer groups, while 1.96% were neutral and 3.92% strongly disagreed.

Table 3 summarizes changes in extension worker competencies and performance after training, with 94.1% of workers introducing training materials to female farmers. Additionally, 82.4% conducted

Table 2. Direction of competency change among extension workers (N=51)

Competency aspect	Indicator	Baseline condition	Post-training evidence	Direction of change
Knowledge	Understanding gender concepts in extension	Gender viewed mainly as women's participation	82.4% discussed gender-based work-time gaps; 100% discussed access and control over resources	Strong cognitive improvement
Attitude	Willingness to initiate gender dialogue with farmer groups	Gender issues rarely discussed openly	82.4% initiated gender discussions	Normative and attitudinal shift
Skills	Facilitation of Business Model Canvas (BMC)	BMC rarely used in extension practice	74.5% facilitated business plan development; 80.4% facilitated new business ideas	Substantial practical skill improvement
	Participatory facilitation techniques	Predominantly directive	92.2% facilitated group discussions and goal-setting of FFGs	High improvement in facilitation skills
	Pluralistic and cross-sector engagement	Limited collaboration beyond public extension	54.9% collaborated; 66.7% discussed cross-sector collaboration	Moderate improvement

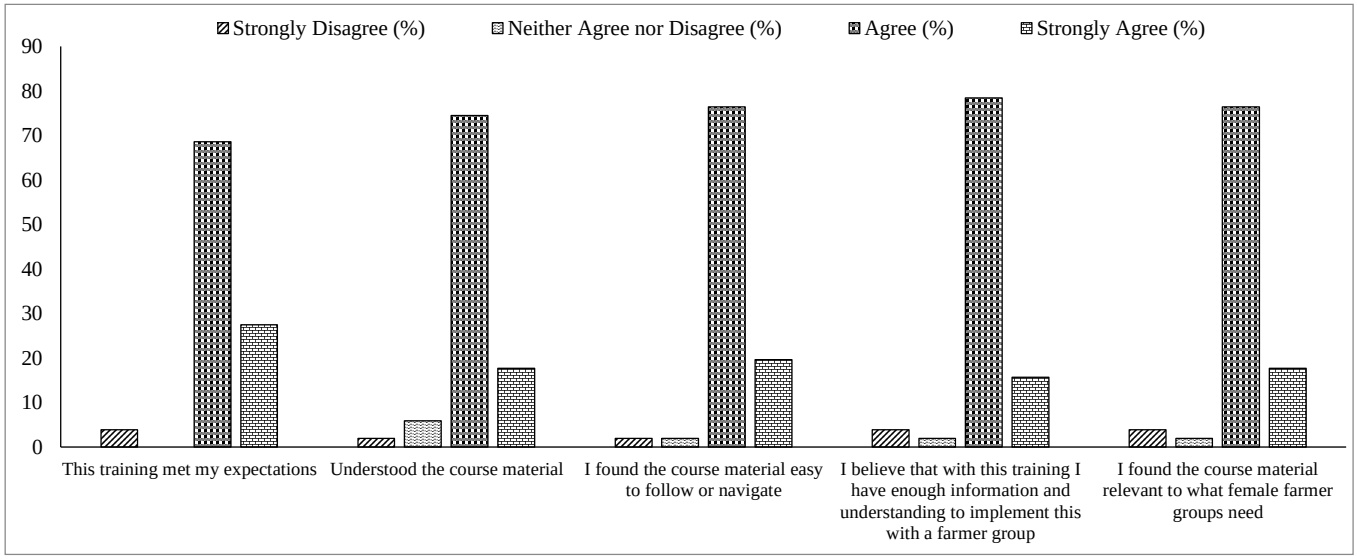


Figure 2. Perceptions of agricultural extension workers regarding the training implementation

Table 3. Changes in extension worker competencies four months after the training and post-training performance achievements

What did the extension workers do after completing the training on the integrative extension approach?	Yes (%)	Not Yet/No (%)
Facilitated training materials with at least one female farmer group	94.1	5.9
Conducted participatory needs assessment with farmer groups	82.4	17.6
Discussed gender differences in farming workloads between men and women	82.4	17.6
Discussed gender-related issues with farmer groups beyond the target groups	66.7	33.3
Discussed differences in access and control over resources between men and women	100.0	0.00
Established communication with external extension partners	58.8	41.2
Discussed cross-sector collaboration to support female farmer groups	66.7	33.3
Collaborated with actors from other sectors in extension activities	54.9	45.1
Facilitated group discussions with female farmer groups	92.2	7.80
Facilitated goal-setting activities with female farmer groups	80.4	19.6
Facilitated discussions on new business ideas	68.6	31.4
Facilitated business plan development using BMC	74.5	25.5

gender analyses on participation and discussed gender gaps in work time within groups.

Beyond primary target groups, 66.7% of extension workers discussed gender issues with other farmer groups, and all extension workers (100%) addressed the gender gap with at least one group. Regarding networking, 58.8% formed new contacts, and 66.7% explored cross-sector collaboration to support FFGs. Direct collaboration with other sectors was reported by 54.9%. Post-training activities on group development and entrepreneurship were common: 92.2% facilitated discussions with female groups, 80.4% helped generate business ideas, 68.6% reported groups starting new activities, and 74.5% helped develop business plans.

DISCUSSION

The training improved participatory facilitation, gender sensitivity, and entrepreneurship through structured modules, experienced facilitators, and interactive methods like discussions and coaching. Studies stress the need to develop facilitation, advisory, and innovation skills in complex agricultural systems (Davis & Sulaiman, 2016; Klerkx & Rose, 2020). Training is an investment for policymakers (Pourjavid et al., 2021). However, gender-sensitive facilitation remains weak, requiring ongoing learning with continuous training, institutional support, and mentoring, not one-off efforts (Ragasa et al., 2019; Lecoutere et al., 2023). The BMC needed more practice and mentoring for effective application in agribusiness. Overall, training outcomes depended on program design, implementation, and post-training support (Stufflebeam & Zhang, 2017; Davis & Sulaiman, 2016).

A higher proportion of female extension workers (FEW) is crucial to advancing FFG empowerment. Of the 51 participants in training, 26 were female. FEW improve women farmers' access to and participation in FFGs by reducing sociocultural barriers and building trust (Nguyen et al., 2021). In Kenya, Fischer & Qaim (2012) reported that collective action in female banana-producing groups, along with other interventions, increases gender equality. In Bangladesh, gender-responsive extension services have also been shown to boost women's empowerment and household income (Islam & Walkerden, 2022).

Regarding the digital infrastructure, although extension workers operate within a stable system, heavy workloads limit their ability to provide intensive support, especially for FFGs. A high number of farmer groups per extension worker reduces performance due to time and energy constraints (Dewi et al., 2025). This highlights the need to combine face-to-face, group, and digital approaches to maintain service quality.

The training improved participatory facilitation and entrepreneurial support via the BMC, with extension workers in four districts applying it with FFGs to assess market-fit products based on group decisions. However, gender-sensitive skills improved modestly, highlighting ongoing challenges with gender norms and decision-making. Findings suggest that gender awareness alone is insufficient without ongoing, transformative learning, as also reported by Wahyuni et al. (2020). High satisfaction with the training materials indicated successful alignment between curriculum design and the actual needs of extension workers.

Participants' confidence in implementing the training increased self-efficacy, a key determinant of training transfer (Ahmadpour et al., 2016). Evidence shows investing in facilitation skills and learning media improves extension performance (Dewi et al., 2025). International research indicates active participation in extension promotes women's empowerment (Das et al., 2023).

The discussion of gender gaps in access and labour division highlights the need for gender-transformative extension practices. Evidence shows that facilitating gender dialogue boosts women's access to extension services and innovations (Diaz & Najjar, 2019; Lecoutere et al., 2023; Snider et al., 2024; Pateriya et al., 2026).

The rise in cross-sector collaboration signals a shift in the roles of extension workers from singular actors to multi-stakeholder platforms. The scholarly literature consistently shows that engaging diverse actors enhances farmer empowerment and strengthens livelihood resilience (Maryono et al., 2024; Timu et al., 2024). The pronounced focus on goal-setting, business planning, and entrepreneurship aligns with findings from agribusiness training initiatives, which underscore the importance of experiential learning and business-oriented facilitation (Kumari et al., 2024).

A limitation of the research is that training was conducted in an area with stable internet access, enabling smooth implementation. This highlights the need to adapt the approach for regions with limited digital infrastructure.

CONCLUSION

An integrated training approach combining participatory, pluralistic, gender-sensitive, and entrepreneurial content strengthens agricultural extension workers' capacity to support FFGs. The results show improvements not only in the conceptual understanding and facilitation skills of the extension workers but also in behavioural outcomes, including increased confidence, stronger self-efficacy, and greater use of the BMC. However, the study highlights persistent institutional and cultural constraints that limit the full implementation of gender-sensitive extension. Despite greater attention to gender and development, challenges remain in addressing structural inequalities and facilitating collective decision-making. Sustaining these gains requires stronger digital advisory tools, expanded multi-stakeholder collaboration, inclusive extension policies, with long-term institutional commitment and support. In practice, the results provide a foundation for developing an online training as a broader, more efficient, and more sustainable capacity-building strategy. Further research needs to test the training's effectiveness across various regional contexts and evaluate its long-term impact.

DECLARATIONS

Ethics approval and informed consent: Informed consent was obtained from the respondents regarding the study during data collection.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The authors declare that during the preparation of this work, they thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Article

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Role of Savings and Credit Groups in Ethnic Minority Household Livelihoods in Ea Drong commune, Vietnam

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HIGHLIGHTS

- Savings and credit groups operate as community-based financial systems suited to resource-constrained rural areas.
- Savings and credit groups mainly support short-term and small-scale livelihood investment rather than replacing formal credit.
- Participation in savings and credit groups strengthens household financial, social, and human capital.

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ABSTRACT

The study was conducted in 2025 to examine the role of savings and credit groups (SACGs) in supporting the livelihood of ethnic minority households in Ea Drong commune, Vietnam. The study analysed the contribution of SACGs to household saving practices and access to credit, examined the use of SACG financial resources in livelihood activities and assessed their contribution to strengthening livelihood assets. The study employed a mixed-methods approach, combining semi-structured interviews with 72 SACG members, two focus group discussions, five in-depth interviews, and secondary data. The findings indicated that SACGs functioned as flexible community-based financial mechanisms that complement formal credit systems in rural areas. Approximately 97.2% of members reported increased annual savings after joining SACGs, while 45.8% accessed loans directly from the groups. Loan amounts ranged from $76.92 to $192.30 and were used for livestock production and essential household expenditures. Although SACGs mainly supported short-term and small-scale financial needs, these groups played an important complementary role in enhancing household resilience and supporting diversified livelihood strategies among ethnic minority households. The study highlighted the importance of integrating SACGs with agricultural extension, financial literacy training, and formal financial services to strengthen rural livelihood development and financial inclusion.

INTRODUCTION

Access to and use of appropriate financial services play an important role in promoting inclusive growth and sustainable poverty reduction (Ha, 2019; Arunkumar et al., 2023). However, a large proportion of the population in developing countries still lacks access to financial services (Bwalya & Zulu, 2021). This gap is particularly evident among rural populations and women, whose access to banking services remains significantly lower than that of urban residents and men (Holloway et al., 2017). Collateral requirements, high transaction costs, seasonal risks, and the inherent uncertainty of agricultural production discourage formal financial institutions from expanding into rural areas (Lopez & Winkler, 2018; Ilesanmi et al., 2024). Community-based financial models,

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commonly referred to as savings and credit groups (SACGs), have emerged as a flexible and accessible alternative. These groups operate based on voluntary participation, self-governance, and internal capital mobilization, allowing members to save regularly, access small loans, and share profits cyclically (Frisancho & Valdivia, 2020; Bwalya & Zulu, 2021; Faizan et al., 2025).

SACGs enhance savings, stabilize consumption, and support agricultural investment, while improving credit access, reducing reliance on informal loans, and strengthening resilience (Ksoll et al., 2016; Bwalya & Zulu, 2021; Zimusi & Moyo, 2024). They also contribute to financial, social, and human capital, and promote women's economic empowerment (Frisancho & Valdivia, 2020; Shinogi et al., 2021; Rajkumar et al., 2024). However, evidence on their impact remains mixed, some studies report gains in income and assets (Ksoll et al., 2016), while others find limited welfare effects (Karlan et al., 2017). Some studies report improvements in income and household assets, whereas others indicate limited long-term welfare effects due to small capital size and weak linkages with formal finance (Chitema & Chitongo, 2020; Oranu, Onah et al., 2020). This study draws on the Sustainable Livelihoods Framework. This framework emphasizes that household livelihoods are shaped by access to different forms of livelihood capital, including financial, social, human, natural, and physical capital, together with the institutional and socio-economic contexts influencing household livelihoods (Chambers & Conway, 1992; DFID, 1999). Within this framework, SACGs are understood not only as community-based financial mechanisms but also as institutions that have the potential to strengthen livelihood assets, enhance household coping capacity, and influence livelihood strategies.

The effectiveness of SACGs remains highly context-specific because socio-economic conditions, institutional environments and agricultural practices differ across regions (Kumari & Malik, 2020; Maurya et al., 2024). Although previous studies in Vietnam have examined rural credit access, microfinance, and financial inclusion among poor and ethnic minority households (Luan & Bauer, 2016), empirical evidence on SACGs as self-governed community-based financial institutions remains limited, particularly in ethnic minority areas. The study aims to examine the influence of SACGs on the livelihoods of ethnic minority households in rural Vietnam through analyzing the role of SACGs in improving household saving practices and access to credit, examining the influence of SACGs on the use of financial resources for livelihood activities, household consumption, and production investment, and assessing the contribution of SACGs to strengthening livelihood assets, particularly financial, social, and human capital among ethnic minority households.

METHODOLOGY

The study was conducted in Ea Drong commune, Dak Lak province, Vietnam, where ethnic minority households depend largely on agricultural livelihoods and face limited access to formal financial services. A mixed-methods approach combining qualitative and descriptive quantitative data was used. Primary information was collected through semi-structured interviews with 72 members of SACGs, two focus group discussions (FGDs), and five in-depth interviews with key informants. A purposive sampling approach was used to select 72 SACG members from different groups within the commune to ensure diversity in gender, ethnicity, and livelihood activities. The sample size was determined based on information saturation, where no major new themes emerged during data collection. Because the study primarily aimed to explore livelihood experiences and perceived changes associated with SACG participation rather than to generate statistically representative estimates, purposive sampling and information saturation were considered appropriate for the study objectives. The semi-structured interview guide was developed based on the study objectives and the Sustainable Livelihoods Framework (Chambers & Conway, 1992; DFID, 1999). The interview themes focused on household livelihoods, saving practices, access to credit, loan utilization, and perceived livelihood changes associated with SACG participation. Two FGDs involving 8–10 SACG members each were conducted to explore livelihood benefits, operational challenges, and social dynamics related to SACG participation. Five in-depth interviews were also conducted with three SACG leaders and two commune-level officials involved in livelihood development and SACG activities. These key informants were selected based on their leadership roles and knowledge of SACG operations within the locality. Secondary information was also collected from commune-level socio-economic reports and related research to supplement the data for this study.

Quantitative data were analysed using descriptive statistics, including frequencies, percentages, means, and standard deviations. Qualitative data from FGDs and in-depth interviews were analysed using thematic analysis to identify major themes related to savings, credit access, livelihood investment, and perceived livelihood changes associated with SACG participation. Findings from different data sources were triangulated by comparing information from semi-structured interviews, FGDs, in-depth interviews, and secondary data to ensure consistency and reliability. The quantitative data were used mainly to provide descriptive support for qualitative interpretation rather than to test causal relationships. Ethical considerations were maintained throughout the research process. All participants were informed about the study objectives and the voluntary nature of participation before interviews were conducted, and informed consent and confidentiality were ensured throughout the study. As the study employed purposive sampling within a single commune, the findings are intended to provide contextualized insights rather than statistical generalization to all ethnic minority communities in Vietnam.

RESULTS

Characteristics of savings and credit group members and livelihood activities

Women constitute a large proportion of the group's members, with over 84% being female. This finding suggests that women play an important role in household financial management within participating households. Regarding ethnic composition, over 79% of the SACGs are Ede people, with the remainder belonging to the Tay and Nung ethnic groups. The average educational level and average age of the members are 7.1 grades and 42.5 years old

Table 1. Participation in Livelihood Activities of Savings and Credit Group Members

Income-generating activities	Quantity
I. Crop cultivation	
Coffee (%)	100
Durian (%)	48.6
II. Animal husbandry	
Goat (%)	19.4
Pig (%)	40.3
Chicken (%)	43.1
Other (%)	8.3
Average household income per year ($/year)	5,605.53 (±905.85)

Note: Values in parentheses indicate standard deviations

respectively (Table 1). This indicates that the group members are literate, proficient in writing and arithmetic, and are in their working years, possessing stable employment and experience in household production and economic management. The participating members represent a diverse range of household types, including not only well-off and middle-income households, but also poor and near-poor households, contributing to increased mutual support among members.

The members of the group are all involved in agricultural production activities, with crop cultivation and livestock farming attracting the largest number of participants. Therefore, this study investigates and analyzes the main income-generating activities of the members to assess their dependence on each specific production activity, and to provide a realistic livelihood analysis of the role of SACGs in supporting livelihoods.

Farming remains the primary livelihood for members of SACGs, with 100% of participating households cultivating coffee, reflecting a high level of dependence on this crop. It is also a characteristic product of the area, closely linked to the culture, lifestyle, and livelihoods of the local people. In addition, nearly half of the members cultivate durian, indicating a trend towards crop diversification to increase income, as well as to meet market demand as durian exports to China expand. In the livestock sector, over 40% of members raise chickens and pigs, while goat farming remains limited. Livestock farming serves as a supplementary income-generating activity (coffee being the main income-generating crop) and is primarily carried out by women, as they can manage both housework and livestock farming at home. These livelihood activities generated an average household income of approximately $5,605.53 per year. However, the large standard deviation reflects significant income disparities among participating households related to household classification, production scale, and the number of livelihood activities undertaken. The diversity of livelihood activities indicates that households adopt diversified livelihood strategies to manage economic and production risks. Coffee cultivation remains the dominant livelihood activity, while livestock farming serves as an important supplementary source of income, particularly for women.

Role of saving and credit groups in improving household saving and access to credit

To address the first research objective, this section examined how SACGs are associated with household saving practices and improve access to credit among ethnic minority households. The analysis focuses on saving behavior, financial accumulation, and patterns of access to formal and informal loan sources. These indicators help describe the potential contribution of SACGs model to household financial security and support for livelihood investment.

The average annual savings of the members reached approximately $90.38, reflecting a modest level of financial accumulation among ethnic minority households (Table 2). However, the large standard deviation indicates considerable variation in saving levels among households. This suggests that although SACGs generally encourage saving behaviour, members differ substantially in their financial capacity and ability to accumulate savings depending on livelihood scale, household income, and economic conditions. Some households are able to save regularly and at higher levels, whereas poorer households mainly contribute small but consistent amounts. Regarding the use of savings, the majority of households prioritize spending on essential family needs such as healthcare and general living expenses, demonstrating the important role of saving in strengthening resilience to socio-economic shocks at the household level. In addition, a significant proportion of members use their savings for livelihood investments, particularly livestock farming, reflecting a direct link between saving and production expansion. Meanwhile, the proportion of households using savings for crop cultivation remains very low. This pattern is closely associated with the gendered division of labor within households, where women are more actively involved in livestock farming while men are primarily responsible for crop cultivation activities. Furthermore, 37.5% of households allocated savings to their children's education, suggesting that SACGs may support long-term investment in human capital. Notably, although 29.2% of households reported being unable to save before joining the group, 97.2% saw an increase in annual savings after joining, indicating a perceived improvement in saving practices and household financial management among participants. The reported increase in savings is based on members' self-assessments and perceived

Table 2. Savings amount and intended use of savings by each member

Category	Quantity
Average annual savings per members. ($/year)	90.38 (±89.61)
Purpose of using savings	
Family expenses (health, general household expenses, etc.) (%)	83.3
Expenses for children's education(%)	37.5
Expenses for livestock farming (purchasing input materials, expanding production, purchasing tools and equipment, etc.) (%)	77.8
Expenses for farming (purchasing inputs, seedlings, etc.) (%)	1.4
Other (%)	4.2
Ability to save before joining a credit savings group	
Yes (%)	70.8
Annual savings increase.	
Yes (%)	97.2

Note: Values in parentheses indicate standard deviations

Table 3. Current Status of Members' Access to Loan Capital

Sources of household loan capital	Quantity (%)
Social Policy Bank	62.5
Commercial banks (Vietcombank, Viettinbank, etc.)	18.1
Savings and credit group	45.8
Supply company/Dealer	5.6
Other sources	2.8

changes in saving behaviour rather than on longitudinal financial records collected prior to participation.

The study synthesizes information on the main loan channels used by households to analyze the extent and structure of access to loan capital for members participating in SACGs. Considering the diversity of loan sources, including formal and informal credit institutions, allows for an examination of the supplementary function of SACGs in household financial access.

The Social Policy Bank is the main formal lending source, accessed by 62.5% of households, underscoring the key role of policy credit in supporting rural and vulnerable groups (Table 3). In contrast, 18.1% of households borrow from commercial banks, suggesting limited access to market-based credit. Regarding the informal channel, up to 45.8% of households use loans from their own SACGs, suggesting that these groups serve as flexible and accessible financial channel for the small-scale and short-term capital needs. Meanwhile, a very small percentage of members borrow through companies or supply agents and other sources. FGD participants consistently emphasized the accessibility and convenience of SACG loans, particularly the absence of collateral requirements and the simplicity of borrowing procedures. There were 87.5% of households, who considered the lack of collateral requirements a significant advantage, considerably reducing the barrier to accessing credit for members with limited resources. Almost all members perceived the loan process from the group as simple and convenient, reflecting the flexibility and suitability of the operating mechanism based on trust and community oversight. These findings indicate that SACGs play an important complementary role in expanding access to loans and supporting short-term and small-scale financial needs among ethnic minority households, rather than replacing formal credit institutions.

"We can borrow directly within the village without collateral or complicated procedures. When livestock get sick or we need feed urgently, the group loan helps us respond immediately" an opinion from a SACG leader

Use of saving and credit group loans in household livelihood activities

Addressing the second research objective, this section analyzes how SACG financial resources are utilized within household livelihood systems and essential consumption needs. Examining the structure of loan utilization allows for an assessment of the livelihood orientation of this capital, as well as the role of SACGs in supporting essential needs and expanding production activities of participating households (Table 4).

With loan amounts ranging from $76.92 to $192.30 per member, the majority of this money was used for livelihood investment, with 77.8% of members using it for livestock farming. This indicates that SACG loans support small-scale production expansion and household income generation. In addition, 69.4% of households used the loan capital for essential family needs such as healthcare and general living expenses. This finding reflects the continued financial vulnerability of many households, where borrowed capital is also necessary to meet basic household needs and unexpected expenditures. Notably, none of the households used the loan capital for crop cultivation or other purposes, suggesting that loan capital from SACGs was primarily directed towards livestock farming and essential expenditures, aligning with their more limited livelihood characteristics and financial needs. In contrast, capital for farming activities such as coffee and durian typically requires significantly larger funding than the amount borrowed from these savings and credit groups. As a result, SACG loans primarily function as mechanisms for consumption smoothing and support for low-cost livelihood activities rather than as capital sources for large-scale agricultural investment.

Table 4. Purposes of using loan capital from the Savings and Credit Group

Category	Quantity (%)
Family expenses (health, general household expenses, etc.)	69.4
Spending on children's education	9.7
Livestock farming expenditures (purchasing inputs, expanding production and business, etc.)	77.8
Expenses for crop cultivation (purchasing inputs, seedlings, etc.)	0.0
Other	0.0

Contribution of saving and credit groups to household livelihood assets

To address the third research objective, this section examines how SACGs contribute to strengthening household livelihood assets, particularly financial, social, and human capital. The findings presented in this section are based on qualitative synthesis and the consensus reached during focus group discussions rather than on standardized quantitative measurement scales (Table 5).

Focus group discussions revealed a strong level of consensus regarding the livelihood benefits associated with SACG participation. Participants consistently emphasized the importance of SACGs in improving access to small-scale local credit, reducing short-term financial pressure, and supporting livelihood-related expenditures. Members highly appreciated the group's role in securing local loan capital and reducing production costs, giving a completely agree rating for both benefits. This reflects the core function of SACGs as a flexible financial mechanism, helping households proactively access timely capital and avoid dependence on high-priced debt purchases. Participants particularly highlighted that SACGs provide easily accessible local loans without collateral requirements, enabling households to obtain capital quickly for small-scale production activities such as purchasing feed, seeds, or veterinary medicines. Many participants also emphasized that immediate cash payments made possible through SACG loans

Table 5. Participants' perceived livelihood benefits from SACG participation

Category	Level of consensus
Local loan sources are available to finance production when needed (for purchasing seeds, feed, veterinary medicine, etc.).	Very high
Production costs can be reduced by avoiding the need to purchase on credit from suppliers (buying on credit is more expensive than buying with cash).	Very high
Production techniques can be improved through sharing among team members.	Very high
Market information is updated through the exchange of information among members.	High
Having a source of savings at the end of the year to spend and reinvest (if needed).	High
Increase knowledge and skills in financial management.	High
Enhance team cohesion and mutual support among members.	High

Note: The levels of consensus presented in the table are based on qualitative synthesis from focus group discussions. The categorization reflects the degree of agreement collectively expressed by participants during discussions

helped households avoid higher costs associated with purchasing agricultural inputs on credit from suppliers.

"Before joining the group, we often bought feed and fertilizers on credit and had to pay higher prices later. Now, when we need money urgently, we can borrow from the group and buy directly with cash, which helps us save costs and feel more secure in production" Opinion from focus-group discussion

Instead of requiring collateral, credit procedures, or traveling to locations where access to loans is necessary, group members can borrow capital right in their village with simple procedures and quick disbursement times. Although limited compared to borrowing from official channels, the savings and credit group contributes to meeting short-term spending needs and is suitable for low-cost investment activities such as purchasing feed, seeds, and veterinary medicine. Improved production techniques, updated market information, enhanced financial management knowledge and skills increased mutual support among group members. These findings suggest that SACGs contribute not only to financial access but also to the strengthening of social and human capital, which participants associate with improved production capacity and livelihood sustainability. However, these findings reflect participants' shared perceptions and qualitative consensus rather than quantitatively measured impact levels, and therefore should be interpreted as indicative rather than statistically generalizable assessments.

DISCUSSION

The findings support previous studies suggesting that SACGs function as community-based microfinance institutions, operating on endogenous capital and self-governance mechanisms (Frisancho & Valdivia, 2020). The organizational structure, regular meetings and transparent loan procedures show that SACGs in Ea Drong operate through relatively institutionalized self-governance mechanisms. This finding supports previous studies showing that SACGs are well suited to rural areas where access to formal credit remains limited (Lopez & Winkler, 2018; Kumari et al., 2020). However, SACGs in Ea Drong do not completely replace the formal financial system but serve as a supplementary mechanism. The Social Policy Bank remains the main lending channel. This is consistent with the argument of Oranu et al. (2020) that SACGs are unlikely to meet large-scale and long-term capital needs. In fact, the loan amount from $76.92 to $192.30/loan is only suitable for small investments, especially in livestock farming, and insufficient for coffee or durian cultivation activities which require large capital. Therefore, SACGs operate as a support mechanism for short-term needs and small input costs, while long-term investment still depends on formal credit. This may explain why, in many empirical studies, the impact of SACGs on long-term income is unclear (Karlan et al., 2017).

SACGs in Ea Drong contribute to strengthening the financial and social capital of participating households. Although the average savings of $90.38/year is modest, 97.2% of members reported an increase in savings after joining the group. This finding is consistent with Ksoll et al. (2016), who reported increased savings among participants in Village Savings and Loan Association models. More importantly, the structure of savings and loan utilization shows that financial resources are directed not only for consumption but also for livelihood investment, especially in livestock farming. This finding highlights the dual role of SACGs in supporting both consumption smoothing and livelihood investment. Therefore, instead of measuring the impact solely through income, SACGs also influence the structure of livelihood strategies (Kumari & Malik, 2020).

Beyond their financial functions, SACGs also contribute to strengthening social and human capital among ethnic minority households. Compared to studies in Africa (Bwalya & Zulu, 2021; Zimusi & Moyo, 2024), the results in Ea Drong show that the groups also facilitate knowledge sharing, market information exchange, and financial management learning among members. This reinforces the argument that SACGs play a role in strengthening social and human capital, thereby enhancing household resilience. However, unlike some evidence suggesting that SACGs can lead to production specialization (Frisancho & Valdivia, 2020), livelihoods in Ea Drong remain diversified (coffee, durian, pig farming, chicken farming, goat farming). Therefore, SACGs in Ea Drong play a crucial role in strengthening short-term financial security, fostering saving habits, supporting small-scale investments, and enhancing social and human capital. However, their ability to promote large-scale livelihood transformation or breakthrough income growth is limited due to the small capital size and dependence on the local economic and social context.

Women play an important role in SACGs, which aligns with previous studies suggesting that SACGs can promote women's economic empowerment through increased access to credit and improved financial management skills (Slathia et al., 2006; Frisancho & Valdivia, 2020; Shinogi et al., 2021; Rajkumar et al., 2024). However, in Ea Drong, women's participation is also linked to the

gender division of labor within households, where women are often the financial managers. Although women constitute the majority of SACG members and actively participate in saving and borrowing activities, the findings indicate that their participation does not necessarily transform traditional gender relations within the household. Women primarily use loans for livestock farming and household expenditures, activities that closely align with socially assigned domestic and caregiving roles. Thus, SACGs mainly strengthen women's financial participation and household financial management roles rather than fundamentally transforming gender divisions of labour. However, regular participation in group activities, financial decision-making, and knowledge sharing may gradually enhance women's self-confidence, social networks, and autonomy in managing household livelihoods. This suggests that SACGs create important spaces for incremental forms of empowerment, even though broader structural gender inequalities remain largely unchanged.

These findings provide implications for rural extension and community-based financial development. Extension workers should integrate SACGs with agricultural extension and financial management training to strengthen household livelihood capacity. Stronger linkages between SACGs and formal financial institutions are also needed to improve access to larger and longer-term agricultural credit. Local authorities should also recognize SACGs as community learning spaces that strengthen social cohesion, livelihood resilience, and women's participation in local economic activities. Therefore, supporting the expansion of SACGs in ethnic minority areas may contribute to broader rural development and financial inclusion strategies. As the study focused on a single commune and relied mainly on self-reported perceptions, the findings should be interpreted as context-specific rather than statistically generalizable. Future research could adopt comparative and longitudinal approaches across multiple regions to further examine variations in SACG effectiveness and their long-term contributions to rural livelihood transformation.

CONCLUSION

The study shows that SACGs not only improve access to small-scale credit but also strengthen the financial, social, and human capital of ethnic minority households. SACGs primarily support short-term financial needs by encouraging saving practices and small-scale livelihood investments, particularly in livestock production, while complementing the formal credit system. The role of SACGs as community-based livelihood support mechanisms that enhance household resilience in resource-constrained rural areas was highlighted. SACGs should be integrated with livelihood training, financial management, and market information-sharing activities, while stronger linkages with formal financial institutions are needed to improve access to larger and long-term agricultural loans. Development programs should strengthen women's participation in livelihood decision-making and community knowledge-sharing activities. Future studies should apply comparative and longitudinal approaches to better examine the long-term impacts of SACGs on household livelihoods and women's empowerment as this study was conducted in an ethnic minority commune and relied on self-reported data.

DECLARATIONS

Ethical approval and informed consent: This study was conducted in accordance with ethical standards. Informed consent was obtained from all respondents prior to data collection

Conflict of interest: The authors declare that they have no conflict of interest

Data availability: The data used in this study are available from the corresponding author upon reasonable request

Author contributions: All authors contributed to the study conception and design. Data collection and analysis were performed by the authors. All authors read and approved the final manuscript

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Research Article

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Adoption of Climate Change Adaptation Practices and Farm Income among Crop Farmers in Hue City, Vietnam

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HIGHLIGHTS

- 65.9% of farmers adopted climate change adaptation practices.
- Climate knowledge, farm size, and distance significantly influence adoption decisions.
- Adoption increases farm income by approximately 35%.
- Knowledge-based extension systems are crucial for effective and inclusive adaptation.

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ABSTRACT

Climate change poses significant challenges to crop production and rural livelihoods in developing countries. This study examines the determinants of climate change adaptation and its association with crop income among farming households in Hue City, Vietnam. Primary data were collected from 337 households in 2025. A binary logit model was applied to analyze adaptation decisions, while an Ordinary Least Squares (OLS) model with robust standard errors was applied to examine income outcomes. The results show that 65.9% of households adopted at least one climate change adaptation practice. Climate knowledge, agricultural land size, and age positively influenced adaptation adoption, whereas distance to economic centers reduced the likelihood of adoption. Adaptation adoption was positively associated with crop income per hectare, with adopters tending to achieve higher income than non-adopters. In addition, skilled labor, community participation, and climate knowledge were positively associated with income outcomes, whereas remoteness showed a negative relationship with income. The findings suggest that climate knowledge, resource endowments, and accessibility conditions are important factors shaping both adaptation behavior and economic outcomes among farming households. The study highlights the importance of strengthening knowledge-based agricultural extension and improving access to information and rural services to support effective climate change adaptation.

INTRODUCTION

The increasing frequency and intensity of extreme weather events, including droughts, erratic rainfall, and heatwaves, have significantly reduced crop productivity, disrupted farming systems, and threatened rural incomes. Empirical evidence consistently shows that climate change not only lowers agricultural yields but also intensifies farmers' vulnerability to environmental and economic shocks (Acevedo et al., 2020; Grigorieva et al., 2023; Islam & Farjana, 2024; Xian-Kang et al., 2024). In response, the adoption of climate change adaptation practices has been widely promoted as a key strategy to enhance resilience and sustain agricultural production. These practices, commonly framed under Climate-Smart Agriculture (CSA), include drought-tolerant crop varieties, adjusted planting calendars, water-saving irrigation, and sustainable land management. Previous studies demonstrate that such practices can mitigate climate risks while improving productivity and farm income (Ma & Rahut, 2024). However, their

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adoption critically depends on farmers' access to relevant information, technical knowledge, and institutional support.

Through extension services, farmers can access climate information, receive technical guidance, and improve their ability to implement appropriate adaptation strategies. However, previous studies suggest that extension access alone does not necessarily result in effective adaptation, particularly when information dissemination is not sufficiently relevant, localized, or responsive to farmers' needs (Davis et al., 2021). In this context, climate knowledge plays a critical role in shaping farmers' perceptions and adaptive behavior. Farmers with better understanding of climate risks and adaptation options are more likely to evaluate the potential benefits of adaptation practices and implement appropriate responses. In this study, extension access is measured as a binary variable indicating whether a household has received extension services, while climate knowledge is measured as a composite index reflecting farmers' understanding of climate change and adaptation practices. Both variables are included in the empirical model to capture their roles in influencing adaptation behavior and crop income outcomes.

The adoption of climate change adaptation practices can be explained using established theoretical frameworks. The Diffusion of Innovations theory (Rogers, 2003) highlights the role of information, perception, and social learning in shaping adoption behavior, while the Random Utility Theory (McFadden, 1972) suggests that farmers adopt new practices when expected benefits outweigh associated costs and risks. Empirical studies consistently identify key determinants of adoption, including education, farm size, access to extension services, and climate information (Finizola e Silva et al., 2024; Shitu et al., 2024; Gashure, 2024; Lamichhane et al., 2022). However, existing research has largely focused on identifying adoption determinants, with relatively limited attention to the mechanisms linking extension systems, knowledge dissemination, and economic outcomes. Evidence indicates that constraints such as limited access to climate information and institutional support continue to hinder effective adaptation among smallholder farmers (Incoom et al., 2025).

In Vietnam, empirical evidence on climate change adaptation at the household level remains limited and fragmented. Existing studies mainly examine factors affecting adoption, while the role of extension systems and climate knowledge in shaping income outcomes remains underexplored (Bien et al., 2022; Ferrer et al., 2023; Nhuong et al., 2025). This gap is particularly relevant in Central Vietnam, where agricultural systems are highly exposed to climate risks and rural livelihoods depend heavily on crop production.

METHODOLOGY

The study was conducted in Hue City, Vietnam, covering both lowland and mountainous agro-ecological zones. These areas are characterized by smallholder-based farming systems that are highly vulnerable to climate variability, particularly droughts and heavy rainfall. Differences in agro-ecological conditions also reflect variations in farmers' access to markets, infrastructure, and agricultural extension services.

Primary data were collected through a structured household survey conducted in 2025 in both lowland and mountainous areas of Hue City, Central Vietnam. A stratified random sampling approach was employed to ensure representation across different agro-ecological conditions. Specifically, the sample was stratified by agro-ecological zones, including lowland and mountainous areas. The sample size was determined using the Yamane (1967) formula at a 95% confidence level and a 5% margin of error, resulting in a target sample of approximately 350 households. A total of 350 households were surveyed, and after data cleaning, 337 valid observations were retained for analysis.

Among the surveyed households, 191 were selected from lowland areas and 146 from mountainous areas. In the lowland zone, 171 households were adopters and 20 were non-adopters of climate change adaptation practices, while in the mountainous zone, 51 households were adopters and 95 were non-adopters. This stratification approach was used to capture differences in agro-ecological conditions and adaptation behavior among farming households. Data were collected through face-to-face interviews with household heads using a structured questionnaire. The questionnaire gathered information on household socio-economic characteristics, production conditions, access to extension services, climate knowledge, adaptation practices, and crop income. Prior to the official survey, the questionnaire was pre-tested with 15 households to assess clarity, reliability, and contextual relevance. Feedback from the pre-test was used to refine and improve the survey instrument before field implementation.

Two dependent variables were defined. First, adaptation adoption (Adapt) is a binary variable equal to 1 if a household adopts at least one adaptation practice, and 0 otherwise. Second, crop income (Income) is measured as annual income from crop production (VND per hectare). Due to skewness, the natural logarithm of income is used in the regression analysis.

The selection of explanatory variables is guided by the Diffusion of Innovations theory (Rogers, 2003) and Random Utility Theory (McFadden, 1972). Accordingly, variables are grouped into four categories: (i) household characteristics (ii) economic resources (iii) institutional and market factors and (iv) perception-related factors.

Household characteristics include age (years), education (years of schooling), labor (number of working household members), and skilled labor (number of members with technical or vocational training). Economic resources are represented by agricultural land (hectares) and distance to economic centers (kilometers), capturing production capacity and accessibility constraints.

Institutional and market factors include extension access, measured as a binary variable (1 = household has received extension services; 0 = otherwise), community participation (1 = participation in local organizations; 0 = otherwise), and market linkage (1 = household has established market connections; 0 = otherwise).

Perception-related factors are captured by climate knowledge, which is constructed as a composite index based on farmers' self-reported understanding of climate change and adaptation practices using a Likert scale. This variable reflects the extent to which farmers internalize and utilize information relevant to adaptation decisions.

Climate knowledge was measured using a composite index constructed from five Likert-scale items capturing farmers' understanding of climate change, awareness of climate-related risks,

perceived changes in temperature and rainfall patterns, knowledge of adaptation practices, and confidence in applying adaptation measures. Each item was rated on a five-point scale ranging from 1 (very low) to 5 (very high).

The climate knowledge index was calculated as the average score across all items, with higher values indicating greater climate knowledge. The reliability of the scale was assessed using Cronbach's alpha, yielding a value of 0.94, indicating good internal consistency. These variables are expected to influence both adoption decisions and income outcomes.

To examine the determinants of adaptation adoption, a binary logistic regression model is employed:

$$P\ (Adaptation_i = 1) = F(ZiY)$$

Where, $Adaptation_i$ denotes the adoption decision of $household_i$; Zi is a vector of explanatory variables; Y is a vector of parameters to be estimated; and F(·) represents the logistic cumulative distribution function.

To estimate the impact of adaptation on farm income, the study applies an Ordinary Least Squares (OLS) model:

$$Ln(Income_i) = \beta_0 + \beta_1 Adaptation_i + \beta_2 X_i + \varepsilon_i$$

Where $Income_i$ represents crop income per hectare of household i; $Adaption_i$ is a binary variable indicating adoption; X_i is a vector of control variables; β denotes parameters to be estimated; and ε_i is the error term. The coefficient β_1 captures the income difference between adopters and non-adopters. Robust standard errors are used to address heteroscedasticity.

RESULTS

The descriptive statistics in Table 1 indicate that farming households are characterized by small-scale production systems and moderate human capital, which are likely to influence both adaptation behavior and crop income outcomes. The average agricultural landholding is relatively small (0.5 ha), confirming the dominance of smallholder farming in the study area. Although limited land size may constrain production capacity, households with relatively larger landholdings may possess greater resources and incentives to invest in adaptation practices.

Education levels remain modest, averaging 7.9 years of schooling, while the number of skilled laborers is relatively low (0.7 persons per household). These characteristics suggest limited technical and managerial capacity, which may reduce farmers' ability to adopt and effectively implement knowledge-intensive adaptation practices. In addition, households are located an average of 7.7 km from commune centers, implying potential difficulties in accessing markets, agricultural inputs, climate information, and extension services. Such accessibility constraints may negatively affect both adaptation adoption and farm income.

Table 1. Socio-economic characteristics of surveyed households

Variables	Mean	Std. Dev.
Age (years)	50.4	10.7
Education (years)	7.9	3.9
Labor (persons)	2.5	0.9
Skilled labor (persons)	0.7	0.7
Agricultural land (ha)	0.5	0.6
Distance to center (km)	7.7	10.2
Credit access (yes=1)	0.7	0.5
Extension access (yes=1)	0.6	0.5
Community participation (yes=1)	0.3	0.4
Market linkage (yes=1)	0.4	0.5
Climate knowledge (Likert 1-5)	2.2	1.2
Crop income per hectare (million VND)	58.1	40.4

Access to institutional support appears moderate, with 70% of households having access to credit and 60% reporting access to extension services. However, participation in community organizations (30%) and market linkages (40%) remains relatively limited, indicating weak social and market integration that may constrain information exchange and economic opportunities. Climate knowledge is also modest, with an average score of 2.2 on a five-point scale, reflecting limited awareness and understanding of climate change and adaptation practices.

Crop income per hectare shows considerable variation across households, with an average of 58.1 million VND per hectare, suggesting substantial heterogeneity in production performance. Overall, the descriptive statistics highlight that resource availability, human capital, climate knowledge, and accessibility conditions are likely to play important roles in shaping households' adaptation decisions and income outcomes.

Adoption of climate change adaptation practices

Figure 1 shows that 65.9% of households adopt at least one climate change adaptation practice, indicating a moderate level of engagement. However, adoption is uneven across practices. Farmers mainly adopt simple and low-cost measures, particularly drought-tolerant varieties (57.6%) and adjustments in planting calendars (40.6%).

In contrast, the uptake of more technical practices remains limited, including soil conservation (23.6%), water-saving irrigation (8.3%), and integrated pest management (6.2%). The adoption of sustainable practices, such as VietGAP and organic farming, is also relatively low (5.9%). Overall, adaptation is concentrated in accessible and less resource-intensive strategies, while more advanced practices are less widely implemented.

Comparison of crop income between adopters and non-adopters

The comparison results in Table 2 reveal a clear and statistically significant difference in crop income between adopters and non-adopters. Households adopting adaptation practices achieve a higher average income (67.5 million VND/ha) than non-adopters (40.1 million VND/ha), with a mean difference of 27.4 million VND/ha.

The independent samples t-test confirms that this difference is statistically significant at the 1% level ($t = 6.21$, $p < 0.01$). This provides strong descriptive evidence that adaptation is associated with improved economic outcomes.

Determinants of adoption of climate change adaptation practices

The logit results (Table 3) indicate that the model is statistically significant (LR $\chi^2 = 221.48$, $p < 0.01$) with strong explanatory power (Pseudo $R^2 = 0.512$). Among variables, climate knowledge, agricultural land size, age, and distance to economic centers are identified as key determinants of adaptation adoption.

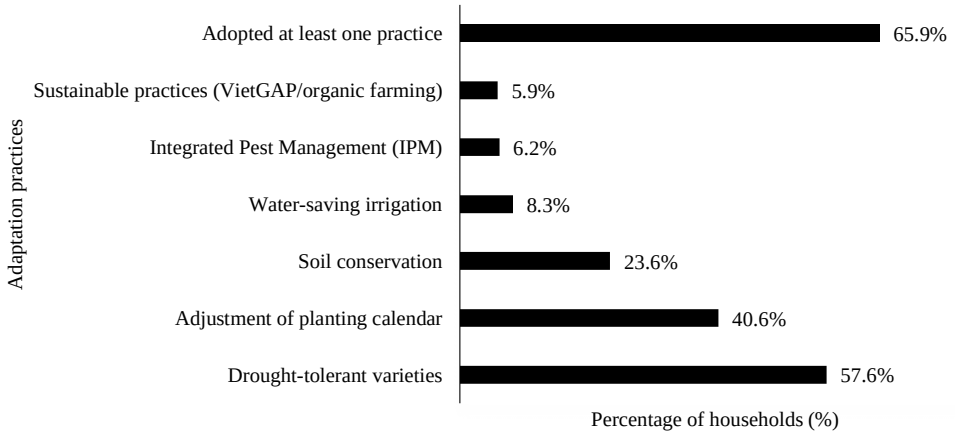


Figure 1. Adoption of climate change adaptation practices among surveyed households
Note: Multiple responses were allowed; therefore, percentages do not sum to 100%.

Table 2. Comparison of Crop Income between Adopters and Non-adopters

Group	Observations	Mean (million VND/ha)	Std. Dev.
Non-adopters	115	40.1	43.5
Adopters	222	67.5	35.5
Difference		27.4***	

t-value = 6.21; p-value = 0.000
Note: *** denotes significance at 1% level.

Climate knowledge is the most influential factor, increasing the probability of adoption by approximately 14.6 percentage points. Agricultural land also has a strong positive effect, raising adoption likelihood by about 26.9 percentage points. Age shows a positive and significant effect, suggesting that more experienced farmers are more likely to adopt adaptation practices.

In contrast, distance to economic centers negatively affects adoption, reducing the probability by approximately 0.96 percentage points per kilometer. Other variables, including education, labor, skilled labor, credit access, extension access, community participation, and market linkage, are not statistically significant among variables.

Impact of climate change adaptation on crop income

The OLS results with robust standard errors presented in Table 4 indicate that the model is statistically significant ($F = 16.73$, $p < 0.01$) and explains a substantial proportion of the variation in crop income per hectare ($R^2 = 0.468$). The relatively low mean VIF value (1.59) further suggests that multicollinearity is not a concern in the model.

Among variables, adoption is positively and significantly associated with crop income ($\beta = 0.350$, $p < 0.01$), suggesting that households adopting at least one climate change adaptation practice tend to achieve approximately 35% higher income per hectare than non-adopters, holding other factors constant. However, this relationship should be interpreted cautiously as an association rather than a strict causal effect due to the cross-sectional nature of the data and the potential presence of selection bias.

Several household and institutional characteristics are also significantly associated with income outcomes. Skilled labor, community participation, and climate knowledge exhibit positive and statistically significant relationships with crop income, highlighting the importance of technical capacity, social networks, and farmers' awareness in improving farm performance. Age is also positively associated with income, suggesting that farming experience contributes to better production outcomes.

In contrast, labor, agricultural land size, and distance to economic centers are negatively associated with crop income per hectare. The negative coefficient of agricultural land ($\beta = –0.411$, $p < 0.01$) indicates that households with larger landholdings tend to obtain lower income per unit of land. Since the dependent variable

Table 3. Determinants of Climate Change Adaptation (Logit Model)

Variables	Coefficient	Std. Error	Marginal Effect	Std. Error
Age	0.062***	0.016	0.006***	0.001
Education	0.067	0.048	0.007	0.005
Labor	-0.016	0.212	-0.002	0.021
Skilled labor	-0.352	0.242	-0.035	0.024
Agricultural land	2.713***	0.817	0.269***	0.076
Distance to center	-0.096***	0.022	-0.010***	0.002
Credit access	-0.153	0.391	-0.015	0.039
Extension access	-0.091	0.386	-0.009	0.038
Community participation	-0.379	0.736	-0.038	0.073
Market linkage	0.735	0.526	0.073	0.051
Climate knowledge	1.476***	0.297	0.146***	0.025
Constant	-5.612***	1.247		

Observations = 337, LR $\chi^2 = 221.48$*** , Prob > $\chi^2 = 0.000$, Pseudo $R^2 = 0.512$
Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$
Marginal effects are reported as average marginal effects.

Table 4. Impact of Climate Change Adaptation on Crop Income (OLS with Robust Standard Errors)

Variables	Coefficient	Robust Std. Error
Adoption (1 = yes)	0.350***	0.108
Age	0.010**	0.004
Education	0.014	0.010
Labor	-0.089**	0.041
Skilled labor	0.179***	0.038
Agricultural land	-0.411***	0.123
Distance to center	-0.027***	0.005
Credit access	0.123*	0.075
Extension access	0.093	0.092
Community participation	0.323***	0.120
Market linkage	-0.048	0.111
Climate knowledge	0.110***	0.034
Constant	3.055***	0.250

Observations = 337, R^2 = 0.468

F-statistic = 16.73*** Root MSE = 0.606Mean VIF = 1.59

*Note: *** p < 0.01; ** p < 0.05; * p < 0.10.*

Dependent variable is the natural logarithm of crop income per hectare.

is measured as income per hectare rather than total household income, this result may reflect differences in land-use intensity and management efficiency across farm sizes. Larger farms may face constraints related to labor allocation, supervision, and input intensity, resulting in lower productivity per hectare compared to smaller and more intensively managed farms.

Distance to economic centers is also negatively associated with income, implying that remoteness limits access to markets, information, and production inputs. Credit access shows a weak positive association at the 10% significance level, while education, extension access, and market linkage are not statistically significant in the model. Overall, the findings suggest that adaptation behavior, human capital, climate knowledge, and accessibility conditions are closely associated with crop income outcomes among farming households.

DISSCUSION

The findings provide consistent evidence that climate knowledge, resource endowments, and accessibility jointly shape both adaptation behavior and income outcomes. Among these factors, climate knowledge emerges as the most influential determinant of adoption, highlighting the critical role of farmers' awareness and understanding of climate risks and adaptation options in decision-making. This result is consistent with previous studies emphasizing the importance of information and learning in promoting climate-smart agriculture (Ma & Rahut, 2024; Mishra et al., 2025).

Importantly, access to extension services alone does not show a significant effect on adoption. This suggests that the effectiveness of extension systems depends less on coverage and more on the quality and relevance of knowledge dissemination. In this context, climate knowledge can be interpreted as a key transmission channel through which extension services influence farmers' behavior (Ghanghas et al., 2015). This interpretation aligns with Patra et al. (2023) and is further supported by Davis et al. (2021), who argue that extension services are most effective when they enhance farmers' knowledge and technical capacity rather than merely expanding access.

Resource endowments also play a key role. The positive effect of agricultural land on adoption indicates that households with greater resources are better positioned to invest in adaptation practices. At the same time, the strong positive impact of skilled labor on income highlights the importance of technical capacity in improving farm performance. This finding is consistent with Abate et al. (2023) and Davis et al. (2021), who emphasize that farmers with higher technical skills are more capable of effectively implementing improved agricultural practices. In contrast, the negative effect of labor suggests diminishing returns or inefficiencies in labor use, implying that labor quality may be more important than quantity.

Accessibility constraints further shape both adoption and income outcomes. The negative effect of distance to economic centers confirms that remoteness limits access to markets, inputs, and information, thereby reducing both the likelihood of adoption and economic performance. This result is consistent with studies highlighting the importance of infrastructure and market access in facilitating technology uptake and improving livelihoods (Finizola e Silva et al., 2024).

The positive association between adaptation adoption and crop income suggests that climate change adaptation practices may contribute to improved farm performance among farming households. Households adopting adaptation practices tend to achieve higher income per hectare, implying that adaptation may help enhance production efficiency and reduce climate-related production risks. This finding is consistent with previous studies showing that climate-smart agricultural practices can generate both economic and environmental benefits for smallholder farmers (Bello et al., 2024; Xian-Kang et al., 2024). However, given the cross-sectional nature of the data, the observed relationship should be interpreted as an.

The negative relationship between agricultural land size and crop income per hectare appears counterintuitive at first; however, it is consistent with the characteristics of smallholder farming systems in developing countries. Because the dependent variable is measured as income per hectare, larger landholdings do not necessarily generate higher land productivity. In many cases, small-scale farmers intensify production through closer supervision, higher labor input, and more efficient use of resources, thereby achieving higher returns per unit of land. In contrast, households with larger farms may face difficulties in maintaining the same level of management intensity and input application across all plots, resulting in lower productivity per hectare.

This finding is consistent with the inverse farm size-productivity relationship widely documented in agricultural economics. Amartya Sen argued that small farms often achieve higher land productivity due to more intensive labor use and closer management (Sen, 1966). Similar evidence has been reported in empirical studies on smallholder agriculture in developing countries, where land expansion is not always accompanied by proportional increases in productivity or income efficiency (Barrett et al., 2010; Larson et al., 2014). The result therefore highlights that improving technical efficiency and resource management may be more

important than farm expansion in enhancing crop income performance.

Finally, the positive effects of community participation and climate knowledge on income highlight the role of social capital and learning in enhancing farm performance. Social networks facilitate information exchange, collective action, and access to resources, thereby improving economic outcomes. Overall, the results suggest a coherent mechanism in which extension systems, through knowledge dissemination, influence adoption behavior, which in turn contributes to improved income outcomes.

The findings suggest several important policy implications. First, improving the quality of agricultural extension services is essential, with greater emphasis on strengthening farmers' climate knowledge rather than simply expanding service coverage. Extension programs should prioritize practical, location-specific, and demand-driven training. Second, targeted support should be directed toward resource-constrained households, particularly those with limited land and technical capacity, to reduce barriers to adopting advanced practices. Third, improving rural infrastructure and market connectivity is critical to mitigate the negative effects of remoteness. Finally, promoting community-based approaches and farmer organizations can enhance knowledge sharing and collective action, thereby strengthening both adaptation capacity and income outcomes. Together, these measures can support more effective and inclusive climate change adaptation in agriculture.

CONCLUSION

The findings reveal that climate knowledge, agricultural land size, age, and distance to economic centers are important factors associated with adaptation adoption. Among these variables, climate knowledge emerged as the strongest predictor, highlighting the critical role of awareness and information in shaping farmers' adaptation decisions. The results also show that households adopting at least one adaptation practice tend to achieve significantly higher crop income per hectare than non-adopters. In addition, skilled labor, community participation, and climate knowledge are positively associated with income outcomes, while remoteness negatively affects both adaptation and farm performance. Policies should focus not only on expanding extension coverage but also on improving the quality, relevance, and accessibility of climate-related information and technical support. Greater attention should also be given to improving rural infrastructure, market access, and support for resource-constrained households, particularly in mountainous areas.

DECLARATIONS

Ethical approval and consent to participate: This study was conducted in accordance with ethical standards. Informed consent was obtained from all respondents prior to data collection.

Conflict of interest: The authors declare that they have no conflict of interest.

Data availability: The data used in this study are available from the corresponding author upon reasonable request.

Author contributions: All authors contributed to the study conception and design. Data collection and analysis were performed by the authors. All authors read and approved the final manuscript.

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Research Article

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Business Intelligence and Decision Making: A Bibliometric Analysis

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HIGHLIGHTS

- Business Intelligence significantly enhances data-driven decision-making and organizational efficiency.
- Research output increased rapidly after 2013, indicating growing academic interest. Artificial intelligence, big data, and machine learning dominate research themes.
- Decision Support Systems emerged as the most influential publication source, whereas, emerging focus includes ethics, sustainability, and human-centric analytics.

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ABSTRACT

The rapid advancement of information and communication technologies fuelled the exponential growth of digitized data, creating new opportunities for research in Big Data Analytics (BDA) and Business Intelligence (BI). This study provided a bibliometric analysis of academic research on the intersection of business intelligence and decision making, drawing on data from the Scopus database between 2010 and January 2025. Using bibliometric tools such as Bibliometrix (R) and Excel, the study examined descriptive analysis and thematic developments. Results revealed that the number of publications had grown significantly since 2013, with Decision Support Systems and related journals serving as primary outlets. Key contributors in this arena included Arnott, Rouhani, and Hou, with the University of Tehran emerging as a leading institution. The United States ranked highest in total citations, while Belgium led in average annual citations. Thematic mapping indicated that data mining, decision makers, and commerce were central "motor themes," while competitive advantage and management systems remained niche topics. Findings confirmed the strategic importance of it in enabling effective decision-making and highlighted emerging research trends in BD, AI, and knowledge management.

INTRODUCTION

Business intelligence (BI) and analytics are key enablers in the digital economy, helping organizations use large data sets for better decision-making and strategic advantage (Davenport & Harris, 2007; Chen et al., 2012; Charkaoui & Jabraoui, 2024). Advances in big data technologies improve efficiency, competitiveness, and long-term performance (McAfee & Brynjolfsson, 2012). Research shows that BI&A supports knowledge-based decisions, predictive analysis, and improved outcomes, while also enhancing organizational agility and decision quality through data-driven insights rather than intuition (Popovic et al., 2012; Delen & Demirkan, 2013). Despite its growing importance, the BI&A field remains theoretically fragmented, overlapping with areas like knowledge management and information systems, leading to varied definitions and approaches (Power et al., 2015). Research confirms its strategic role in driving innovation and resilience, whereas, a clear understanding of its intellectual development is still limited (Popovic et al., 2012; Arnott & Pervan, 2014). To address this, the study analyses BI and decision-making

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research from 2010 to 2025, highlighting key publications and thematic trends (Zupic & Cater, 2015; Aria & Cuccurullo, 2017).

As data analytics underpins BI by converting structured and unstructured data into actionable insights through processes like cleaning, analysis, and modelling. It includes three types: descriptive (past), predictive (future), and prescriptive (actions) (Sharda et al., 2021). So, recent advances in augmented analytics, using machine learning and natural language processing, enable automated, real-time insights via dashboards and models (Shmueli & Koppius, 2011; Henke et al., 2018), making analytics a key driver of innovation and efficiency (Davenport, 2013). Consequently, the integration of advanced analytics into organizational process has reshaped decision-making in contemporary business environments. While traditional models focused on problem identification and evaluation of alternatives, modern approaches rely heavily on analytical tools and predictive techniques. This shift has improved accuracy, transparency, and accountability in organizational decisions. The emergence of decision intelligence, which integrates analytics, artificial intelligence (AI), and behavioral insights, further enhances decision outcomes in complex environments (Arulmanikandan et al., 2025).

In this context, the growing strategic importance of data-driven decision-making has accelerated the evolution of BI systems and technologies within organizations. It has evolved from basic reporting tools to integrated platforms combining data warehousing, mining, analytics, and visualization. It now serves as a strategic capability, helping organizations turn data into actionable insights and support digital transformation through technologies like AI and big data. However, research remains fragmented, often addressing technical and organizational aspects separately.

Notwithstanding its strategic importance, BI&A remains theoretically fragmented, overlapping with fields such as knowledge management and information systems (Arnott & Pervan, 2014; Power et al., 2015; Ain et al., 2019; Akter et al., 2022; Suman et al., 2025). Accordingly, this study employs bibliometric analysis to examine BI and decision-making research from 2010 to 2025. By mapping the field's conceptual structure (Donthu et al., 2021), the study provides a comprehensive view of its development and emerging directions, offering an integrated perspective on BI research (Cobo et al., 2011; Aria & Cuccurullo, 2017; Roy et al., 2024; Jiao et al., 2025; Malawani et al., 2025) over fifteen years.

METHODOLOGY

This study adopts an inductive research approach, deriving conclusions from the analysis of evidence obtained from bibliometric data. The focus is to evaluate the global research output on the impact of Business Intelligence (BI) on Decision Making by applying bibliometric and visualization techniques (Mekimah et al., 2024; Udeh et al., 2024). In doing so, the study focuses on identifying the most significant academic sources, including leading journals and publication outlets, as well as recognizing highly influential documents that have shaped the trajectory of research in this field. Data for the study were collected from major scholarly databases, primarily Scopus (Elsevier), using a structured query with the keywords "Decision Making" AND "Business Intelligence" limited to Title, Abstract, and Keywords for the period 2010 to January 2025. The retrieved records were exported in. bibtex format for Scopus to ensure compatibility. Furthermore, the study investigates the evolution of research themes by tracing their development over time, highlighting both established and emerging directions. This temporal analysis provides insights into how the field has transitioned from foundational concepts to more advanced and integrated approaches. This Data cleaning eliminated duplicates, harmonized metadata, and prepared the dataset for analysis. Using the Biblioshiny package in R, records were converted into .xlsx format separately and merged into a consolidated dataset with the command write.xlsx (combine, file_name = "combine.xlsx"). R libraries such as xlsx, fBasics, and bibliometrix were initialized for the process. The cleaned dataset was analysed with Bibliometrix (R-package) and Microsoft excel, focusing on performance analysis-annual publication trends, influential document, sources, keywords and thematic developments. Visualization techniques such as tables, charts, graphs, thematic maps, and word clouds were used to present publication growth, emerging themes, and frequently used keywords with the help of biblioshiny and VOSviewer. Finally, results were evaluated for accuracy, precision, and recall, with bibliometric indicators cross-verified across databases to ensure reliability and minimize bias.

RESULTS

Evolution of the publications

The year wise publications and citation trends in the area of "Business Intelligence and Decision making" are shown separately by different colour. As shown in Figure 1. year 2024 is having highest in number of citations whereas the 2010 is leading in context to publications.

Most relevant sources

The most relevant sources in the area of "Business Intelligence and Decision making" are the Decision Support Systems with 56 publications, followed by Journal sustainability with 41 publications, followed by intelligence studies in Business with 29 publications, as shown in Table 1.

Word cloud (Keyword plus)

The frequency distribution of keywords is presented in Figure 2. The network visualization highlighted AI as the central research theme, strongly connected with areas like machine learning, big data,

Table 1. Most Relevant Sources

Sources	Articles
Decision Support Systems	56
Sustainability (Switzerland)	41
Journal of Intelligence Studies in Business	29
Journal of Decision Systems	26
Industrial Management and Data Systems	20
Technological Forecasting and Social Change	20
European Journal of Operational Research	19
International Journal of Production Research	19
International Journal of Information Management	18
Journal of Cleaner Production	16

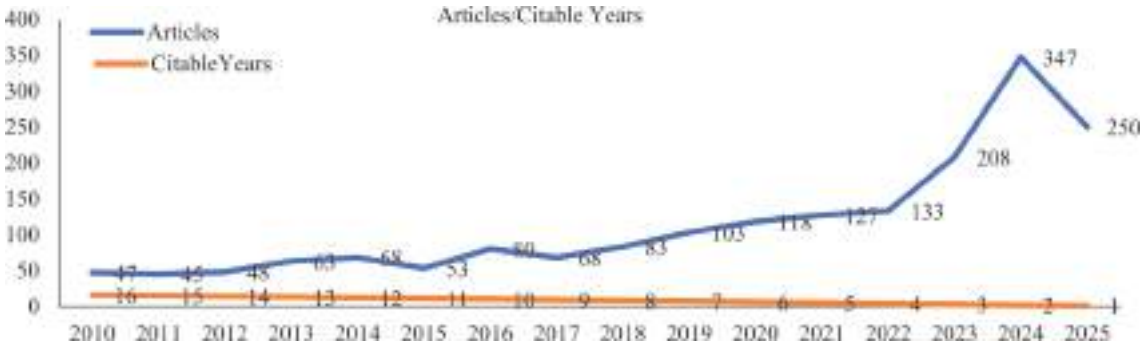


Figure 1. Year Wise Publication and Citation 2010-2025

Table 2. Most Global Cited Documents

Paper	Journal	DOI	TC	TC per Year	Normalized TC
G, 2011	Annual Review of Psychology	10.1146/annurev-psych-120709-145346	2639	175.93	30.40
YK, 2021	International Journal of Information Management	10.1016/j.ijinfomgt.2019.08.002	2521	504.20	37.25
MM, 2015	Journal of Big Data	10.1186/s40537-014-0007-7	2011	182.82	29.38
T, 2021	Journal of Cleaner Production	10.1016/j.jclepro.2021.125834	788	157.60	11.64
W, 2013	International Journal of Information Management	10.1016/j.ijinfomgt.2013.01.001	707	54.38	14.12
NA, 2022	The International Journal of Human Resource Management	10.1080/09585192.2020.1871398	658	164.50	20.75
BP, 2012	User Modeling and User-Adapted Interaction	10.1007/s11257-011-9118-4	656	46.86	11.97
SL, 2020	Business Process Management Journal	10.1108/BPMJ-10-2019-0411	642	107.00	19.20
ADFS, 2021	International Journal of Information Management	10.1016/j.ijinfomgt.2020.102225	528	105.60	7.80
H, 2010	Computers & Operations Research	10.1016/j.cor.2009.11.009	429	26.81	8.76



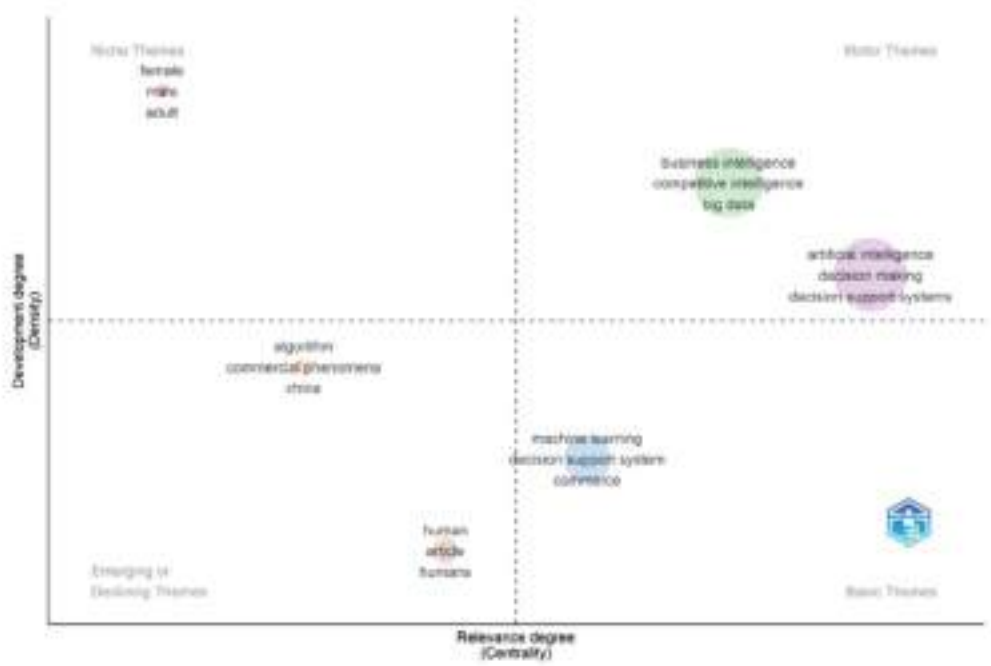
Figure 2. Word Cloud (Keyword Plus)

decision support systems, and competitive intelligence. The clusters reveal that AI research extends beyond technology to applications in business strategy, sustainability, healthcare, and data analytics. A significant stream also emphasized the human and psychological aspects such as cognition, trust, motivation, and emotional intelligence, indicating a shift toward human-centered AI. Emerging themes like ethics, transparency, and sustainable AI suggest growing attention to responsible use of AI. Overall, the map illustrated AI's interdisciplinary nature, bridging technology, management, and social sciences.

Conceptual structure

The thematic map categorized research themes based on their relevance (centrality) and development (density). The motor themes quadrant highlights *business intelligence*, *competitive intelligence*, and *big data* along with AI, *decision making*, and *decision support systems*, showing them as well-developed and highly relevant to the field. The cluster "business intelligence, competitive intelligence and big data" suggests a well-established research program where the relationship between organizational intelligence practices and large-scale data analytics has been thoroughly explored. The high density indicates strong theoretical and methodological coherence among these concepts; the high centrality reveals that this cluster influences and connects with numerous other topics in the field. In the same quadrant the cluster "AI, decision making and decision support systems" occupies a position that is central but slightly closer to the quadrant boundary, suggesting it is a consolidated motor theme with strong relevance. The tight internal linkage among AI, decision-making processes, and support systems reflects a long-standing and productive research tradition. Its centrality confirms that this cluster acts as a backbone topic from which many other research lines branch out. Finally, the strategic significance of the motor themes is that it should be sustained and further expanded, as they represent the field's identity and vitality. They are the themes that attract the most attention, generate the most impact, and provide conceptual scaffolding for the entire domain of the current research.

Figure 3. Thematic Map



Basic themes such as *machine learning, commerce,* and *decision support systems* have high centrality but are less developed, indicating their foundational role. The combination of above-mentioned themes suggests a broad and transversal research front concerned with the application of ML techniques to support commercial and business decisions. The high centrality confirms that this topic underpins and connects many other research areas like, linking to AI, big data, business intelligence. However, the low density indicates that this research front is still consolidating its theoretical frameworks, methodological standards, or conceptual boundaries.

Niche themes like *female, male,* and *adult* are specialized but less connected to the broader domain. This cluster points toward a demographic framing likely studies examining gender and age-related dimensions within the broader field e.g., gender differences in decision-making supported by AI, or demographic segmentation in business intelligence applications. The niche positioning suggests that while this line of research has developed its own internal consistency and scholarly community, it has not yet been integrated into the mainstream discourse of the field. It remains a specialized subfield with limited dialogue with other thematic clusters. Therefore, it is concluded from this quadrant that efforts to build bridges between this demographic/human-factors perspective and core themes (e.g., decision-making, machine learning) could elevate its relevance and centrality.

Meanwhile, emerging or declining themes highlights the line of inquiry concerning algorithmic applications in commercial contexts with a geographic focus on China. The low density suggests that the conceptual relationships among these keywords have not yet crystallized into a coherent research program. The low centrality indicates that this topic has not yet established meaningful connections with the field's core themes. In addition to it the cluster consisting of keywords human, article and humans appears to be a residual cluster, possibly resulting from generic indexing terms rather than substantive thematic content. The inclusion of terms like article and the redundancy of human/humans suggest that this cluster may

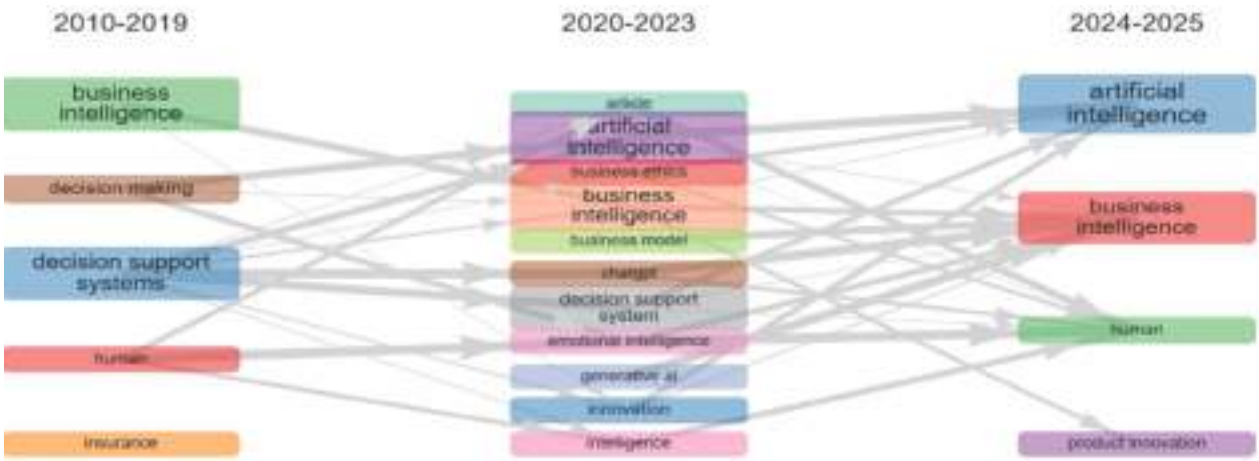


Figure 4. Thematic Evolution Map

reflect bibliographic objects rather than a genuine intellectual theme. Alternatively, it could represent a loosely defined humanistic or human-centered perspective that has not achieved sufficient conceptual articulation. So, these themes require careful monitoring. Overall, the map reveals that AI and business intelligence dominate the research landscape, while human-focused and regional themes remain peripheral. In the next section following the thematic map analysis, the thematic evolution map has been examined across three time slices to understand the progression and transformation of research themes over time.

Thematic evolution

The thematic evolution map showed a clear shift in research focus over time. During 2010–2019, themes such as *business intelligence, decision making, decision support systems,* and *human* dominated. In 2020–2023, the field expanded with the emergence of AI, *business ethics, business models, emotional intelligence, generative AI,* and *innovation,* reflecting a diversification of themes. Moving into 2024–2025, research has consolidated around AI, *business intelligence, human,* and *product innovation,* highlighting the growing emphasis on AI-driven applications, ethical and human-centered approaches, and innovation in business. This evolution indicates a transition from traditional decision-support research to more advanced, AI-driven, and innovation-oriented themes. Further, the themes have been analyzed on the basis of three time slices.

The thematic map for Time Slice 1 showed four quadrants based on the relevance (centrality) and development (density) of themes. “Decision support systems,” “AI,” and “decision support system” are motor themes highly developed and essential to the discipline. “Business intelligence” and “competitive intelligence” are basic themes relevant but less developed. “Female,” “male,” and “priority journal” appear as niche themes well-developed but less central. Themes like “decision-making” and “risk assessment” fall into the emerging or declining category, suggesting limited current development or relevance. The presence of “human” and “article” also indicates marginal and less-developed focus areas. The thematic map for Time Slice 2 revealed a more evolved and diversified research landscape. “Business intelligence,” “big data,” and “decision makings” emerge as motor themes, indicating strong centrality and development. “AI,” “decision making,” and “decision support systems” are basic themes still highly relevant but needing further development. Niche themes like “business ethics,” “COVID-19,” and “fintech” show focused yet less central research. Emerging or declining themes include “ChatGPT,” “sentiment analysis,” and “neural network,” indicating new or fading interests. Topics like “digital transformation” and “sustainability” also highlight growing interdisciplinary interest in technological integration.

The thematic map for Time Slice 3 indicated a consolidation of research themes. “Business intelligence,” “decisions makings,” and “big data” stand out as motor themes, representing well-developed and highly relevant areas. “AI,” “decision making,” and “machine learning” remain basic themes, central to the field but requiring deeper development. “Sustainable development” appears as a niche theme, showing high specialization but limited centrality. Meanwhile, themes like “product innovation” and “data-driven culture” fall into the emerging or declining quadrant, suggesting either new, underdeveloped topics or waning research interest. Overall, the focus is shifting toward applied intelligence and data-centric strategies.

DISCUSSION

This section presents and critically discusses the results of the bibliometric analysis based on publication trends, keyword clusters, thematic evolution, and thematic analysis.

In the contemporary business environment, data is a critical organizational asset (Yeoh & Koronios, 2010), and the integration of BI and Big Data (BD) enhances strategic decision-making and competitive advantage. This integration improves organizational agility and supports long-term sustainability (Adewusi et al., 2024). BI is increasingly converging with AI and advanced analytics, reflecting a shift toward predictive and prescriptive decision-making (Baesens et al., 2016; Mariani & Wamba, 2020). Overall, this evolution highlights a transformation in how organizations leverage data, while also revealing nuanced gaps and areas for further exploration.

The convergence of BI with AI and advanced analytics, as noted by George et al. (2022), reflects a shift toward predictive and prescriptive decision-making. While this improves agility and responsiveness, it also raises concerns related to data privacy, algorithmic bias, and over-reliance on automated insights. Despite rapid technological progress, ethical and interpretability issues remain underexplored (Mariani & Wamba, 2020). Although transparency, accountability, and fairness are widely emphasized (Nwaimo et al., 2023), stronger implementation frameworks are required to effectively apply these principles.

The emergence of ethics, sustainability, trust, and emotional intelligence in BI research reflects a shift toward human-centric and socially responsible approaches. While this aligns with broader corporate social responsibility trends, their practical integration into BI applications and organizational policies remains limited. The key challenge is translating these insights into actionable guidelines that balance innovation with ethical responsibility. The shift from infrastructure-focused research to innovation and digital transformation, as noted by Divatia et al. (2021) and Shehzad & Rozan (2024), reflects the maturity of BI and its alignment with dynamic business environments. It highlights BI’s evolution beyond data warehousing and decision support toward value creation and agility. However, this transition may overlook the importance of data quality, governance, and organizational culture, which are essential for sustaining competitive advantage.

The rise in BI publications after 2013, driven by technological advancements and expanding digital data environments (Delen & Demirkan, 2013; Liang & Liu, 2018; Ain et al., 2019; López-Robles et al., 2019), reflects growing scholarly interest. Although thematic mapping into motor, emerging, basic, and niche themes provides a structured understanding of the field, it may oversimplify BI’s interdisciplinary nature. The diversity of research approaches and publication types (Gaardboe & Svarre, 2018; Wyskwarski, 2019) suggests that a single thematic framework may not fully capture its complexity. The move toward stronger collaboration in recent BI research, contrasting earlier single-author dominance (Rahman et al., 2021), reflects its increasingly collaborative nature. Analysis

across 2010–2019, 2020–2023, and 2024–2025 shows a progression from infrastructure to innovation and value creation. However, strict temporal categorization may overlook overlapping trends and developments that extend across periods.

The integration of BDA and decision intelligence, highlighted by highly cited studies (Riipa et al., 2025), reinforces their role in improving organizational performance and decision accuracy (Nweke & Owusu-Berko, 2025). AI-driven solutions further enhance BI by enabling real-time insights and supporting proactive decision-making (Ganesan & Gopalsamy, 2019; Eboigbe et al., 2023; Kumari et al., 2024; Rostamzadeh et al., 2025; Barman et al., 2026). However, these advancements also raise concerns around data governance, security, and interpretability. Organizations must address these challenges to fully leverage BI while maintaining ethical and operational integrity. The BI landscape reflects rapid technological growth, rising scholarly interest, and increasing attention to ethical and strategic issues. The shift toward predictive, prescriptive, and socially responsible BI is promising but requires balancing innovation with ethical governance, organizational culture, and interdisciplinary collaboration (Marshall et al., 2015). Addressing these challenges will demand adaptive and responsible approaches to sustain progress in BI (Corte-Real et al., 2017; Liang & Liu, 2018; López-Robles et al., 2019; Di Vaio et al., 2022; Alzghoul et al., 2024).

CONCLUSION

The study establishes that Business Intelligence has evolved into a strategic enabler of data-driven decision-making and organizational performance during 2010–2025. The findings highlight the dominant role of AI, big data, and analytics in shaping modern decision processes, while also emphasizing the growing importance of ethical and human-centric approaches. Although the research landscape shows significant expansion, variations in thematic development indicate the need for balanced attention to emerging and foundational areas. The study suggests that future research should adopt interdisciplinary approaches and integrate technological advancements with organizational and social considerations. The results provide valuable insights for researchers and practitioners to understand the evolving role of BI in enhancing decision-making effectiveness and strategic outcomes.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the respondents and their organisations regarding the study during the course of the data collection.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors declare that during the preparation of this work, thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Determinants of Farmers' Willingness to Participate in Wheat Seed Contract Farming in Punjab, India

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HIGHLIGHTS

- Social influence and trust shape farmers' decisions through participation in meetings, peer observation, local group influence, company reputation, and prior contract farming experience.
- Production proficiency encourages adoption by improving farm productivity, enabling convenient marketing, and ensuring access to high-quality seeds.
- Market assurance boosts farmers' confidence by ensuring assured markets, timely payments, stable income, reduced uncertainty, and comparative advantages over non-contract farming.
- Institutional support and incentives strengthen farmers' participation by providing training and capacity-building opportunities, regular technical inspection, and higher price.

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ABSTRACT

The study conducted during 2025 aims to identify the key factors influencing wheat farmers' willingness to adopt wheat seed contract farming. Four major constructs were identified: social influence and trust, market and income stability, production and marketing efficiency, and institutional support and incentives, comprising sixteen significant factors. Among these, social influence and trust emerged as the most important dimensions, explaining 26.32% of the total variance. This construct is primarily driven by observing other farmers (0.941), participation in meetings (0.909), influence of local farmer groups (0.872), company reputation (0.810), and prior contract farming experience (0.809). The second construct, market and income stability, explains 22.27% of the variance and includes assured markets (0.905), smooth payment systems (0.918), stable income (0.911), comparative advantages (0.796), and reduced market risk (0.785). Production and marketing efficiency accounts for 17.21% of the variance, highlighting productivity gains (0.964) and access to quality seed (0.952). Lastly, institutional support and incentives explain 14.89% of the variance, with training (0.963), technical inspection (0.948), and better pricing (0.815) emphasized. Overall, these findings highlight that farmers' participation is shaped by social trust, economic stability, production efficiency, and institutional support.

INTRODUCTION

Agriculture remains the backbone of food security, rural livelihoods, and economic development in developing nations. This holds true for India, where the farm sector has always remained central to the country's sustenance and food security. Punjab, located in northwestern India, occupies a distinctive position in the country's agrarian system due to its high irrigation coverage, extensive mechanization, and favorable agro-climatic conditions. Despite its relatively small geographical area, the state is also a perennially significant contributor to food grains in the country (Mann, 2017; Singh et al., 2020), especially wheat and rice. Indian

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agriculture is characterized by the prevalence of marginal and small farmers, who account for 85% of the farming population and own almost 47% of agricultural land (NABARD, 2025). In the case of Punjab, semi-medium and medium farmers are also highly exclusive due to land concentration in their hands (68.6% of operational holdings are behind them), and 33% (i.e., small and marginal) farmers own a negligible 10% of cultivated land (Gulati et al., 2021). Despite this comparative advantage, farmers continue to face increasing production and marketing challenges, particularly in seed production, including difficulties in meeting quality standards, timely access to inputs, and unstable market prices. These persistent issues have renewed policy and academic interest in "supermarket model" institutional arrangements aimed at reducing uncertainty and improving market coordination for farmers. Previous research studies indicate that contract farming can enhance farm efficiency, reduce transaction costs, and stabilize incomes by mitigating market and price risks (MacDonald et al., 2004; Otsuka et al., 2016; Liu et al., 2020). Meeting the future food grain requirement of 310 MMT by 2030 will depend significantly on the input of productivity enhancers and superior seed quality (Kumar et al., 2016). PAU plays a significant role in the development and dissemination of wheat seed, and it alone produces around 3,000·00 tons of different wheat seed (its bit vague) every year. Most of the seed produced is multiplied and marketed under contract farming with either public or private sector companies registered with the Punjab State Seed Certification Authority (PSSCA) (Sharma et al., 2013; Gajbhiye et al., 2014). Contract farming in Punjab has been extensively studied in the context of high-value horticultural crops; empirical evidence on wheat seed contract farming remains limited. This research gap is especially glaring in the case of wheat, a strategic value for which seed companies are increasingly concentrated in three districts Bathinda, Mansa, and Sri-Muktsar Sahib. Moreover, the bulk of previous studies have focused on economic implications, and little is known about attitudes and decision-making behavior regarding wheat seed. In this context, the study examines the following underlying factors of farmers' participation in wheat seed contract farming, with particular emphasis on social trust, production skills, and market guarantees. The study offers insights into how institutions and social and economic factors coalesce to influence farmers' decisions to contract, and it has important implications for policy-making, seed companies, and agricultural development strategies.

METHODOLOGY

The researcher employed a scheduled survey method, and the survey was conducted in 2025. A multistage sampling design, combining simple random and purposive sampling techniques, was used to collect the necessary data. In the first stage, three private contract farming companies were selected purposively based on their engagement with a relatively large number of contract farmers and their operational focus on wheat, a crop of strategic importance. These companies are primarily concentrated in the districts of Bathinda, Mansa, and Sri Muktsar Sahib, ensuring adequate representation of major contracting entities in the study region. In the second stage, a sample of 419 wheat seed contract farmers was drawn from a population of 900 farmers associated with the selected companies using Taro Yamane's (1967) formula, considering a 5% margin of error and a 95% confidence level to ensure statistical representativeness, consistent with approaches adopted in earlier studies (Rashid et al., 2026; Kumar et al., 2026). This was followed by proportionate sampling to achieve balanced representation across all three contract farming arrangements. The study is primarily based on cross-sectional primary data collected through a structured questionnaire administered to wheat seed-producing farm households. In total, the study covered 13 development blocks (Tehsils) across three different districts of Punjab - Bathinda, Mansa, and Sri Muktsar Sahib, located in the Malwa region, from which respondents were randomly selected. Additionally, to boost the survey instrument's credibility and reliability, a pre-test was conducted on a pilot survey of 30 respondents outside the sample area. The researcher's assessment of internal consistency employed Cronbach's alpha, which yielded a value of 0.755, exceeding the acceptable threshold of $\geq$0.70. Thereby indicating satisfactory reliability of the measurement scale (Ray et al., 2021).

The data's goodness-of-fit was tested before PCA was applied. The KMO sample adequacy test and Bartlett's sphericity test were used to determine whether the correlation matrix was suitable for factor analysis. KMO value of 0.708 and statistically significant Bartlett's K-Square ($P < 0.05$) are recommended for PCA analysis in this dataset (Yadav et al., 2026; Yadav et al., 2026). Subsequently, PCA was performed on the standardized correlation matrix.

This method decomposes the total offering into linear combinations of the original variables, where each principal component being orthogonal to the others and accounting for a smaller share of the total variance. For component extraction, Caesar's criteria were used, retaining components with eigenvalues greater than 1, where the Eigen's value (l) reflects the average number of clauses interpreted by each construct, obtained from the following equation.

$$Rv = \lambda v \quad \text{... (1)}$$

Where, R is the correlation matrix, v is the eigenvector, and λ is the eigenvalue. To improve the explanation, Varimax orthogonal rotation was applied, reordering the variance among the residual components while keeping them unrelated. The variables with factor weights greater than 0.60 were considered essential contributors to the component. Depending on the rotating factor load, components were assigned to the group with the highest load. The component score for each family was calculated using the regression method, as expressed below:

$$Si = W1\ Zi1 + W2\ Zi2 + ... + Wk\ Zik \quad \text{... (2)}$$

Where Si, i^{th} is a component score for the ith family, Zij reflects standardized variable values, and Wj represents the component loads. These scores were later used for descriptive and comparative analyses across households, and this was verified using CFA afterwards. A model fit analysis was performed to assess the hypothesized model's goodness of fit, followed by the development of the confirmatory model.

Also, four items were used to investigate farmers' perceptions about contract farming, while two were used to solicit farmers' financial risk perceptions. During the data collection, respondents ranked their level of agreement with each perception statement. A

farmer who highly disagreed with a particular risk statement was assigned a value of –1, disagreed was assigned –0.5, neutral was assigned 0, agreed was assigned 0.5 and highly agreed was assigned 1. Following (Avane et al., 2012; Amrago & Mensah, 2023) the simple arithmetic mean was used to compute the farmer's perception index as follows:

$$\text{Perception index} = \frac{\Sigma\pi}{N} \quad ...(3)$$

Where, N is the number of perception statements, and is the mean score for each perception statement, which is estimated as:

$$\pi = \frac{\Sigma \text{Frequency1} \times \text{Wieght1}}{n} \quad ...(4)$$

Where n, denotes the number of respondents.

RESULTS

Table 1 presents farmers' perceptions of private-sector wheat seed contract farming across four dimensions. Social influence and trust emerge as strong drivers, with around 75–80% of farmers acknowledging the role of peer interactions, meetings, local groups, company reputation, and prior experience (mean = 0.452). Similarly, production and marketing efficiency are perceived positively, as nearly three-fourths of respondents noted improved productivity, convenient marketing, and better access to quality seeds (mean = 0.452). In contrast, market and income stability reflects weaker confidence (mean = 0.210), with only about 43% agreed on assured markets, with many remaining neutral regarding payment and income stability. Institutional support and incentives showed moderate agreement (mean = 0.291), particularly regarding training, technical support, and better prices. Overall, the grand perception index (0.346) indicates a moderately favorable attitude, suggesting that while farmers generally recognize the structural benefits of contract farming despite some concerns about market stability.

Table 3 presents the EFA results, revealing four latent constructs: Social Influence and Trust, Production and Marketing Efficiency, Market and Income Stability, and Institutional Support and Incentives. All indicators exhibit strong standardized factor loadings (>0.60), confirming good convergent validity.

The Social influence and trust construct is defined by five key indicators peer influence, participation in meetings, local farmer groups, company reputation, and prior contract farming experience highlighting the importance of social learning and institutional credibility in shaping adoption decisions. Production and marketing efficiency captures productivity gains, convenient marketing, and access to quality seed, reflecting the operational advantages provided by contract farming. Market and income stability encompasses assured markets, smooth payment systems, stable income, reduced market risks, and comparative advantages, emphasizing the role of contractual arrangements in minimizing uncertainty. Institutional Support and Incentives includes access to training, technical support, and better pricing, indicating the supportive role of firms in enhancing farmers' capabilities.

Institutional support and incentives is portrayed in access to training, facilities of technical support during pre- and post-production periods, and higher incentive price than normal market

Table 1. Summary of farmers' motivation to join private contract

Perception statements	Mean
Social influence and trust	
Participation in farming related meetings has influenced my decision to adopt contract farming.	0.43
Observing other farmers has positively influenced my decision to engage in contract farming	0.49
Local farmers' groups have influenced my decision to adopt contract farming.	0.41
The company's trustworthiness and reputation have positively influenced my decision to opt for contract farming.	0.12
Prior experience with contract farming has influenced my decision-making.	0.38
Perception score	0.452
Production and marketing efficiency	
Contract farming enhances farm productivity.	0.46
Contract farming facilitates convenient and efficient marketing procedures.	0.48
Contract farming ensures access to high-quality seeds.	0.54
Perception score	0.452
Market and income stability	
Contract farming ensures access to a guaranteed market.	0.27
Contract farming has relative advantages over non-contract farming.	0.37
Contract farming provides a stable and predictable income.	0.10
Contract farming reduces the risks associated with market uncertainty.	0.28
Perception score	0.210
Institutional support and incentives	
Contract farming provides access to training and capacity-building opportunities.	0.26
Contract farming facilitates regular technical inspection and monitoring.	0.15
Contract farming offers prices higher than the Minimum Support Price (MSP).	0.39
Perception score	0.291
Grand perception index	0.346

Table 2. Exploratory Factor Analysis

Contract farming dimensions	Loadings	Cronbach's alpha (α)	Composite reliability (CR)
Social influence and trust			
Participation in farming related meetings has influenced my decision to adopt contract farming.	.909	.919	.939
Observing other farmers has positively influenced my decision to engage in contract farming	.941		
Local farmers' groups have influenced my decision to adopt contract farming.	.872		
The company's trustworthiness and reputation have positively influenced my decision to opt for contract farming.	.810		
Prior experience with contract farming has influenced my decision-making.	809		
Production and marketing efficiency			
Contract farming enhances farm productivity.	.966	.965	.972
Contract farming facilitates convenient and efficient marketing procedures.	.964		
Contract farming ensures access to high-quality seeds.	.952		
Market and income stability			
Contract farming ensures access to a guaranteed market.	.905	.912	.936
Contract farming facilitates timely and smooth payment mechanisms.	.918		
Contract farming provides a stable and predictable income.	.911		
Contract farming reduces the risks associated with market uncertainty.	.785		
Contract farming offers comparative advantages over non-contract farming	.796		
Institutional support and incentives			
Contract farming provides access to training and capacity-building opportunities.	.963	.897	.936
Contract farming facilitates regular technical inspection and monitoring.	.948		
Contract farming offers prices higher than the Minimum Support Price (MSP)	.815		
Single-factor bias (Herman approach, 26.32%)			

Table 3. Discriminant validity

	Social trust	Production and marketing efficiency	Market and income stability	Institutional support and incentives
Social trust	0.823			
Production and marketing efficiency	0.131	0.950		
Market and income stability	0.101	0.042	0.796	
Institutional support and incentives	0.084	0.058	0.040	0.886

Table 3 reports the Fornell–Larcker discriminant validity matrix for the four latent constructs: Social Trust, Production Proficiency, and Market Assurance.

make contract farming an attractive institutional arrangement for seed producers of wheat. The reliability test also supports the robustness of the measurement model. All constructs have Cronbach's alphas greater than the suggested cut-off value of 0.70, indicating strong internal consistency among the measurement items. Composite reliability of the constructs also lies within the acceptable range, supporting the rigor and stability of the constructs as indicated by the indicators. The Fornell–Larcker criterion test was conducted for discriminant validity as presented in Table 3. The square roots of the AVE for each construct are greater than the inter-construct correlations. This implies that the constructs are empirically distinct and that they measure distinct concepts. The relatively low correlations among the constructs (ranging from 0.040 to 0.131) suggest that farmers clearly differentiate between social, production, market, and institutional dimensions when evaluating contract farming. This distinction reinforces the multidimensional nature of farmers' perceptions and confirms that each construct captures a unique aspect of their decision-making process.

The Confirmatory Factor Analysis (CFA) results confirm a strong and statistically significant measurement structure across all four latent constructs, with all factor loadings being positive and significant ($p < 0.001$). Social Trust shows high loadings (0.614–0.990), emphasizing the importance of peer interactions, meetings, and prior experience, consistent with earlier findings. Production Efficiency exhibits very strong loadings (0.920–0.969), indicating a robust construct aligned with farmers' positive perceptions of productivity, marketing convenience, and input access. Market and Income Stability shows greater variability in its loading (0.526–0.986), reflecting the mixed perceptions, particularly regarding income stability and risk reduction, which corresponds to the lower mean scores observed in the descriptive analysis. Finally, Institutional Support also demonstrates strong loadings (0.649–0.94+), confirming the relevance of training, technical support, and pricing incentives. Overall, the CFA results validate the constructs and are consistent with the descriptive findings.

DISCUSSION

The study's primary purpose is to understand the different dimensions of contract farming from the farmers' perspective. The research identified and validated four major construct, which include

Table 4. Confirmatory factor analysis

Latent variables	Estimate	Std.Err	z-value	P(>|z|)	Std.lv	Std. all
Social trust =~						
ST1	1.380	0.049	28.083	0.000	1.380	0.990
ST2	1.121	0.057	19.599	0.000	1.121	0.796
ST3	1.392	0.053	26.1863	0.000	1.392	0.953
ST4	0.746	0.051	14.692	0.000	0.746	0.644
ST15	0.891	0.064	13.846	0.000	0.891	0.614
Production efficiency =~						
PME1	0.978	0.036	27.037	0.000	0.978	0.969
PME2	1.046	0.039	26.633	0.000	1.046	0.961
PME3	0.936	0.038	24.629	0.000	0.936	0.920
Marketing and income stability =~						
MIS1	1.072	0.041	26.295	0.000	1.072	0.952
MIS2	1.034	0.037	28.052	0.000	1.034	0.986
MIS3	0.951	0.035	26.871	0.000	0.951	0.963
MIS4	0.628	0.055	11.511	0.000	0.628	0.526
MIS5	0.658	0.055	11.928	0.000	0.658	0.542
Institutional support =~						
IS1	1.428	0.050	28.726	0.000	1.428	1.011
IS2	1.383	0.054	25.565	0.000	1.383	0.949
IS3	0.911	0.061	14.850	0.000	0.911	0.649

Notes: =~ indicates factor loadings of observed variables on latent constructs. Std. Err denotes standard error; Std. all represents fully standardized loadings. All estimated loadings are statistically significant ($p < 0.01$).

16 factors that influence farmers' decisions to adopt wheat seed contract farming. In the social dimension, participation in meetings, observing fellow participating farmers, motivation from local farmer groups, the reputation of contracting companies and previous contract farming experiences emerge as the most powerful factors influencing the decision to join contract farming. Farmers also gain information on contracting agencies and the volume to be contracted through attending these meetings, thereby mitigating informational deficiencies and moral hazard problem. Such exchanges facilitate trust in the contracting relationship by enabling farmers to share concerns on prices, quality specifications, and terms of delivery (Bijman, 2008). And then, watching other growers who are already under contract is a form of social learning within the peanut policy environment. Favourable experiences lower perceived risk and encourage adoption through the demonstration effect and social imitation (Kumar & Singh, 2010; Nain & Kumar, 2010; Schewe Stuart, 2016, Vellema et al., 2019; Arouna et al., 2021; Mao et al., 2022). Knowing the contracting firms is also an essential aspect for building farmers' trust. Also, knowledge of contracting companies trust-building were essential issues among farmers. It is those companies with a good reputation, fair practices in treating farmers, on-time payments, clear explanations of the terms of payment for procurement that are considered more competitive in attracting farmers under contract (Mao et al., 2022; Pham et al., 2026). Past experience enhances farmers' capacity to make informed decisions regarding efficient profitable production and marketing strategies. In particular, experience with contract farming emerges as a significant determinant influencing farmers' transition from traditional to more commercialized farming systems (Ba et al., 2019). A strong institutional reputation signals credibility and reduces concerns about opportunistic behavior, lowers transaction costs and strengthens long-term contractual relationships (Singh et al., 2025). Prior studies have shown that farmers' production and marketing decisions are strongly influenced by peers' observed behaviour through information sharing, demonstration effects, and informal learning (Pham et al., 2026). We expect the peer effect instrument to affect an individual farmer's probability of contracting with a private firm by influencing how they evaluate benefits and risks, as well as the credibility of contracts. Furthermore, significant predictors of contract farming participation among farmers include farm productivity, convenience and speed of selling produce, and access to good seed under the production and marketing proficiency dimension. Contract farming improves farm productivity by encouraging the use of advanced production technologies, uniform cultivation methods, and promptly addressing production requirements. Through embedded services such as technical supervision and input, and the transfer of the final product to the company premises, with proper coordination between the firms and farmers, farmers' tendency towards contract farming is boosted. The study's findings align with those of Key and Runsten (1999) Swinnen and Maertens (2007), Saroj et al. (2023), who found that contracting firms reduce production inefficiencies and enable farmers to achieve higher, more consistent yields. These coordinated procurement mechanisms significantly enhance production efficiency by streamlining post-harvest operations and reducing transaction costs. By simplifying the selling process, farmers can focus on production decisions and avoid unnecessary marketing decisions, thereby contributing to a decline in farm efficiency (Warning & Key, 2002; Bellemare, 2016). Contracting firms are directly connected with agricultural institutions, enabling them to obtain first-hand, high-quality seeds. These are distributed to farmers through local contracting arrangements, which in turn

reinforce farmers' linkages and dependence on contracting firms. The provision of good-quality seed increases biological productivity, reduces fear of crop failure, cognitive dissonance about low yields and qualitative rejections, and transaction costs that poor farmers experience in meeting contracts (Birthal et al., 2007). In the market and income stability dimension, indicators including smooth payment mechanisms, income stability, assured market access, comparative advantages, and mitigation of market uncertainty demonstrate factor loadings exceeding the acceptable threshold, identifying them as critical determinants of farmers' participation in contract farming. The majority of private-sector firms operate in close proximity to farming areas, fostering strong farmer–firm relationships that enable flexible financial arrangements. Farmers generally procure foundation seed without upfront payment, as the cost is adjusted against the final settlement. Furthermore, farmers may seek advance financial support from contracting firms to facilitate the purchase of agricultural inputs, the studying findings are aligned with Khalili et al. (2024) who found that timely buyer payments can act as determinants of trust. A fixed price and assured market can provide a compelling economic incentive to reduce income and unpredictable market risks. Khalili et al. (2024) and Birthal et al. (2005) reported that price advantages significantly reduce market risk for farmers, thereby facilitating their participation in contract farming. Given these characteristics of contract farming, farmers find it more profitable than traditional farming. Rusu et al. (2024) found that access to credit, improved technologies, and enhanced production skills significantly mitigate price volatility risks, while stable income constitutes a major benefit of contract farming.

The institutional support and incentives dimension comprise three key components: access to training, technical inspection, and the provision of prices higher than those prevailing in local markets. Technical training is essential for enhancing productivity and strengthening farmers' technical capacity through the adoption of improved agricultural practices. Moreover, timely monitoring of crop germination and growth plays a critical role in improving crop performance. Contract farming companies facilitate higher productivity, improved quality compliance, and greater cost efficiency by providing extension services, training, and regular field supervision. Such technical support not only enhances farmers' production capabilities but also reduces information asymmetry and production risks, thereby positively influencing farm-level decision-making (Warning & Key, 2002; Bellemare, 2016; Kujur et al., 2026).

CONCLUSION

The study identifies four key dimensions social influence and trust, production and marketing efficiency, market and income stability, and institutional support as critical drivers of farmers' participation in wheat seed contract farming. Within the social trust dimension, participation in meetings, observation of fellow farmers, influence of local farmer groups, reputation of contracting firms, and prior contract farming experience collectively play a crucial role in reducing uncertainty, building trust, and encouraging adoption. Economic incentives, including assured markets, stable income, and reduced price risks, render contract farming more attractive than traditional systems. Institutional support through training, technical supervision, and financial facilitation improves farmers' capabilities and decision-making. These finding offer practical implications for policymakers, agribusiness firms, and extension agencies regarding the implementation of trust-based mechanisms, and effective production support services. Finally, the findings suggest that a viable and sustainable contract farming model should be structured to promote farmers' participation and increase income and food security.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the respondents and their organisations regarding the study during the course of the data collection.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors declare that during the preparation of this work, thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Aspirations of Farm Science Students in Odisha: A Comparative Analysis across Agricultural Disciplines

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HIGHLIGHTS

- Farm science undergraduates showed moderate aspirations in education, jobs, self-employment, socio-economic and economic domains.
- Veterinary science students reported higher aspirations, while gender differences reflected women's focus on higher studies and men's preference for entrepreneurship and income.
- Findings call for tailored academic support and career counselling to align with student aspirations in agriculture and allied fields.

ARTICLE INFO

Keywords: Farm science students, Aspirational levels, Career aspirations, Entrepreneurship development, Skill development, Agricultural education.

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ABSTRACT

Designing successful educational initiatives and policy interventions requires an understanding of these goals. 160 undergraduate students from the fields of agriculture, veterinary science, fisheries science and agricultural engineering participated in the current study at Centurion University of Technology and Management (CUTM), Odisha during 2025. The study had five main aspects of aspirations: economic, socioeconomic, self-employment, job and education. The results showed that most students in all subjects had moderate aspirational levels. Fisheries students had medium levels of educational aspirations, followed by veterinary science (65.00%), agriculture (60.00%) and agricultural engineering (57.50%). Eighty percent of veterinary science students and about sixty-five percent of students from the other disciplines expressed a medium level of enthusiasm for job. Seventy percent of students in agriculture and fisheries, sixty-seven percent in veterinary science and twenty-eight percent in agricultural engineering expressed a moderate desire to work for themselves. Students studying agriculture had the highest socioeconomic aspirations (92.50%), followed by fisheries (75.00%), veterinary science (67.50%) and agricultural engineering (65.00%). The study reveals significant differences in aspiration levels among students in various farm science fields and offers insightful information to help politicians and educational institutions create plans that promote students' professional and entrepreneurial development.

INTRODUCTION

Aspirations are strong motivators that influence young people's academic and career paths. Aspirations for undergraduate students seeking degrees in agriculture, veterinary, fisheries and agricultural engineering represent their socioeconomic and personal aims in addition to their academic and professional objectives. These aspirations have an impact on students' academic engagement, career choices and final contributions to society and the agricultural industry (Lekang et al., 2016; Lekang et al., 2017; Vishwakarma et

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al., 2025). While students' employment expectations emphasize their preferred careers in government, private or entrepreneurial domains, their educational aspirations direct their desire for further education and advanced learning opportunities (Sikdar & Prakash, 2025). While socio-economic ambitions highlight their interest in enhancing family welfare, obtaining social recognition and aiding in community development, self-employment aspirations show their propensity for independent endeavours, especially in agri-based businesses (Genicot & Ray, 2020). Students' life choices are greatly influenced by their economic goals, which are strongly linked to their financial security and job security, particularly in fields related to agriculture that are essential to the development of the country (Sebastian, 2021). However, there are clear differences between fields and gender, which calls for further research.

Designing successful educational initiatives and policy interventions requires an understanding of the goals of agriculture science students. In addition to influencing professional choices, aspirations also have an impact on academic achievement, skill development and entrepreneurial orientation (Arunachalam et al., 2020). Many agricultural graduates are becoming less interested in traditional farming and government occupations in favor of jobs in the private sector, agribusiness or non-agricultural fields (Vinodkumar & Seema, 2021; Raju & Devarani, 2023). Programs for rural development and agricultural extension networks will be significantly impacted by this change. The state of Odisha, which is renowned for its agrarian economy and diverse agroclimatic conditions, has made significant advancements in agricultural education through institutions that provide a range of farm science programs.

Moreover, there exists a noticeable gap between academic training and industry requirements, leading to issues such as unemployment, underemployment and lack of entrepreneurial skills among graduates (Modak et al., 2018; Meena et al., 2018). Despite the significance of this issue, empirical studies focusing on the aspirations of farm science students, particularly in Odisha, remain limited. In light of this, the current study was carried out to evaluate the economic, socioeconomic, job, educational and self-employment goals of farm sciences undergraduate students. By examining these aspects, the study aims to offer knowledge that will help colleges, decision-makers and career advisors match academic programs and support networks with students' goals, strengthening their position in agriculture and related fields (Kosec & Khan, 2016). In this regard, the current study was conducted to evaluate the economic, socioeconomic, occupational, educational and self-employment goals of Centurion University of Technology and Management, Odisha undergraduate students majoring in agriculture science. For the study undergraduate students from the fields of agriculture, veterinary science, fisheries science and agricultural engineering participated in the study. Knowing these goals is crucial to figuring out what drives students to pursue professional growth, entrepreneurship and career advancement in agriculture and related fields (Kim et al., 2015). Additionally, it is anticipated that the study's conclusions will give educational institutions, legislators and career counsellors important information about how to match academic programs and support networks with students' goals (Meinam et al., 2023). In addition to meeting the changing labour and skill needs of the industry in India, such alignment will improve students' readiness for new opportunities and challenges in agricultural and related industries (Arun Kumar et al., 2021).

METHODOLOGY

A cross-sectional descriptive and comparative study was conducted during 2024–25 at Centurion University of Technology and Management (CUTM), Paralakhemundi, Odisha. CUTM was purposively selected because it is among the few private skill-focused universities in eastern India offering all four undergraduate farm science programmes viz. B.Sc. (Hons.) Agriculture, B.V.Sc. & A.H., (Veterinary Science), B.F.Sc. (Fishery Science) and B.Tech (Agricultural Engineering) under a single institutional roof, enabling direct disciplinary comparison under a uniform institutional environment. The study is grounded in Genicot and Ray's (2020) Aspiration Theory, which holds that aspirations function as endogenous reference points embedded within social networks. When aspirations are within a feasible reach of one's current position, they motivate effort and investment; when they exceed perceived capacity, they may generate frustration or disengagement. This framework guided both the selection of aspiration domains and the interpretation of moderate aspiration levels observed in the study. The sampling frame consisted of all final-year and pre final year undergraduate students enrolled in the four disciplines at CUTM during 2024-25. Final-year and pre final year students were targeted because they are most proximate to career decision-making and are likely to hold crystallized aspirations. The total enrolment across disciplines constituted the population (N = approximately 200). A sample of n = 160 was drawn using proportional simple random sampling, with allocation proportional to discipline enrolment size: Agriculture (n = 40), Veterinary Science (n = 40), Fishery Science (n = 40) and Agricultural Engineering (n = 40). Within each discipline, students were selected by systematic random sampling from the department register. The resulting sample was 64% male (n = 102) and 36% female (n = 58), broadly reflecting the enrolment composition at the institution. The scale comprised five Likert-type subscales, each measuring one aspiration domain (educational, job, self-employment, socio-economic and economic). Each item was rated on a 5-point scale (1 = Strongly Disagree to 5 = Strongly Agree). Aspiration levels were classified into three categories Low, Medium and High using the Mean ± Standard Deviation (SD) criterion, a widely accepted method in extension education research (Arunachalam *et al.*, 2020; Meinam et al., 2023. Chi-square (χ^2) tests of independence were used to test for significant associations between (a) discipline and aspiration level categories, and (b) gender and aspiration level categories.

RESULTS

Aspirations of farm science students according to their discipline

Agricultural science

Table 1 shows how aspirations are distributed among farm science students by subject. Most students in the agriculture subject showed medium levels in every aspiration component. Just 10% of the students had high educational aspirations, while 60%

Table 1. Distribution of farm science students according to their aspirations

S.No.	Component	Category	Score	Frequency	Percentage	
Agricultural Science						
1	Education Aspiration	Low	<7	12	30.0	Mean=7.7; SD=0.7
		Medium	7-8.4	24	60.0	
		High	>8.4	4	10.0	
2	Job Aspiration	Low	<12	9	22.5	Mean=13.6; SD=1.6
		Medium	12-15.2	27	67.5	
		High	>15.2	4	10.0	
3	Self-employment Aspiration	Low	<15.6	5	12.5	Mean=17.2; SD=1.6
		Medium	15.6-18.8	28	70.0	
		High	>18.8	7	17.5	
4	Socio- economic Aspiration	Low	<9.3	3	7.5	Mean=10.2; SD=0.9
		Medium	9.3-11.1	34	85.0	
		High	>11.1	3	7.5	
5	Economic Aspiration	Low	<6.6	2	5.0	Mean=7.8; SD=1.2
		Medium	6.6-9	33	82.5	
		High	>9	5	12.5	
Veterinary Science						
1	Education Aspiration	Low	<15.7	6	15.0	Mean=18.5; SD=2.7
		Medium	15.7-21.36	26	65.0	
		High	>21.36	8	20.0	
2	Job Aspiration	Low	<11.8	4	10.0	Mean=13.5; SD=1.7
		Medium	11.8-15.2	32	80.0	
		High	>15.2	4	10.0	
3	Self-employment Aspiration	Low	<14.3	6	15.0	Mean=16S; D=1.7
		Medium	14.3-17.7	27	67.5	
		High	>17.7	7	17.5	
4	Socio- economic Aspiration	Low	<10.6	5	12.5	Mean=12.6; SD=2.0
		Medium	10.6-14.6	27	67.5	
		High	>14.6	8	20.0	
5	Economic Aspiration	Low	<6.6	2	5.0	Mean=7.8; SD=1.2
		Medium	6.6-9	33	82.5	
		High	>9	5	12.5	
Fishery Science						
1	Education Aspiration	Low	<16.9	3	7.5	Mean=19.7; SD=2.8
		Medium	16.9-22.5	30	75.0	
		High	>22.5	7	17.5	
2	Job Aspiration	Low	<12	9	22.5	Mean=13.6; SD=1.6
		Medium	12-15.2	26	65.0	
		High	>15.2	5	12.5	
3	Self-employment Aspiration	Low	<15.5	5	12.5	Mean=17.2; SD=1.7
		Medium	15.5-18.9	28	70.0	
		High	>18.9	7	17.5	
4	Socio- economic Aspiration	Low	<9.6	5	12.5	Mean=11.7; SD=2.1
		Medium	9.6-13.8	26	65.0	
		High	>13.8	9	22.5	
5	Economic Aspiration	Low	<6.6	2	5.0	Mean=7.8; SD=1.2
		Medium	6.6-9	33	82.5	
		High	>9	5	12.5	
Agricultural Engineering						
1	Education Aspiration	Low	<7	13	32.5	Mean=7.7; SD=0.7
		Medium	7-8.4	23	57.5	
		High	>8.4	4	10.0	
2	Job Aspiration	Low	<12	10	25.0	Mean=13.6; SD=1.6
		Medium	12-15.2	26	65.0	
		High	>15.2	4	10.0	
3	Self-employment Aspiration	Low	<15.6	5	12.5	Mean=17.2; SD=1.6
		Medium	15.6-18.8	28	70.0	
		High	>18.8	7	17.5	
4	Socio- economic Aspiration	Low	<9.6	5	12.5	Mean=11.7; SD=2.1
		Medium	9.6	26	65.0	
		High	>13.8	9	22.5	
5	Economic Aspiration	Low	<6.6	2	5.0	Mean=7.8; SD=1.2
		Medium	6.6-9	33	82.5	
		High	>9	5	12.5	

of the students fell into the medium category. In a similar vein, only a tiny percentage of students (10.00-12.50%) expressed strong job aspiration, while the majority of students (67.50%) had medium levels. Similar trends were seen in the students' aspirations for self-employment, with only 17.5% having high aspirations and 70% falling into the medium category. When it came to socioeconomic aspirations, the majority of students (85.0%) had medium aspirations, with 82.50% of students in the medium category and only 5% in the low category, economic desire had the largest concentration. These findings indicate that agriculture students generally possessed moderate levels of aspiration across educational, job, self-employment, socioeconomic and economic dimensions, with relatively fewer students exhibiting high aspiration levels, particularly in educational and work aspirations (Joaquim, 2022).

Veterinary science

The findings on the aspirations of veterinary science students showed that the majority of respondents had medium-level goals for each of the components. The majority of students (65%) had medium educational aspirations, while 20% had high expectations, showing that a reasonable percentage were pursuing higher education. Only 10% of respondents had high expectations, indicating a modest propensity towards career goals, whereas 80% of respondents had job aspirations that were heavily focused in the medium category. The majority of veterinary science students felt medium goals for self-employment (67.5%), despite 17.5% having high expectations. Socioeconomic aspirations showed similar patterns, with 20% falling into the high category and 67.5% into the middle level. While the medium category had the highest concentration of economic aims (82.5%), just 12.5% of students reported having high ambitions. Veterinary students generally showed a propensity toward moderate aspirations in all areas, with comparatively fewer students aiming at higher levels, however socioeconomic and educational dimensions showed a much larger inclination towards high expectations than others (Bysted & Hansen, 2015).

Fishery science

The analysis of ambitions among fisheries students revealed that most students had medium-level aspiration in all categories. A moderate but balanced inclination for additional education is shown by the fact that 75% of respondents had medium educational goals and 17.5% had high hopes. Similar trends were seen in students' job expectations, with only 12.5% displaying high goals and 65% falling into the medium category. Seventy percent of students had medium-range expectations for self-employment, whilst 17.5% had high aspirations. According to socioeconomic ambitions, 65% of students fell into the midrange category followed by 22.5% of students aimed for higher levels and low 12.5%. The medium group has the highest concentration of economic aspirations (82.5%), whereas just 12.5% had high goals. Overall, the results show that students studying fisheries have a tendency to have modest goals in a variety of fields, with comparatively few students aiming higher, especially in the economic and employment domains (Hari et al., 2013).

Agricultural engineering discipline

The analysis of agricultural engineering students' aspirations shows that the majority of respondents expressed medium levels in most domains. Only 10% reported having high aspirations, indicating very modest educational aims, whereas the majority of respondents (57.5%) had medium expectations, with a significant 32.5% falling into the low category. Additionally, the majority of job aspirations (65%) fell into the medium category, with only 10% falling into the high category and 25% into the low category. Seventy percent of students had medium goals for self-employment, while just 17.5% had high aspirations. The distribution of socioeconomic goals was similar, with 22.5% aiming for higher levels and 65% in the medium category. Just 12.5% of students showed high expectations, but 82.5% of students were in the medium category with the highest concentration of economic aspirations. Overall, the expectations of agricultural engineering students were primarily moderate throughout several domains, with comparatively fewer students aiming for higher levels, especially in the areas of education and employment.

Overall aspiration levels of farm science students across disciplines

The results showed that most students in all farm science courses had medium levels of overall aspirations, which reflected balanced and moderate future aspiration. There were fewer

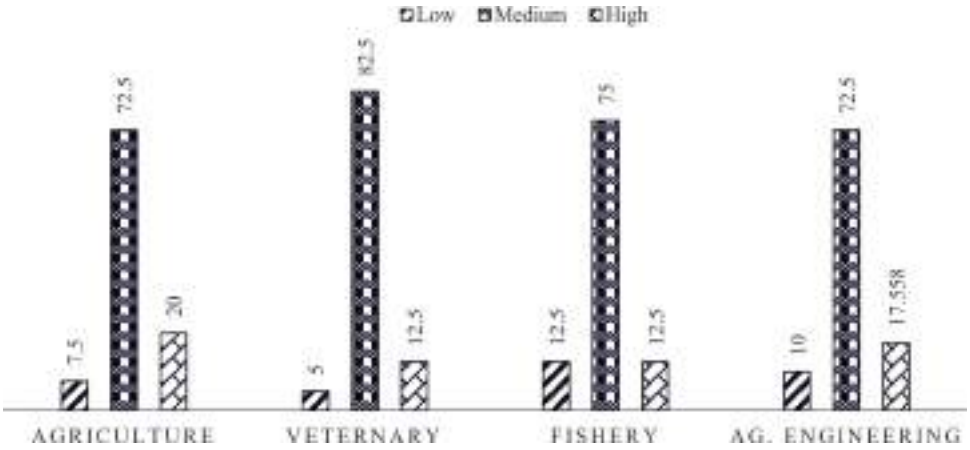


Figure 1. Overall aspiration of Farm science students

responders in the low and high aspiration groups, with the majority of students from agriculture, fishery and agricultural engineering falling into the medium aspiration category. The findings are consistent with those of Mann et al. (2020), who also found that farm science students had moderate aspiration levels.

However, veterinary science students exhibited a comparatively higher proportion in the high aspiration category than students of other science disciplines, indicating greater motivation and ambition towards their future goals and aspiration. This finding suggests that, although medium aspiration levels predominated overall, veterinary students possessed relatively higher aspirations regarding educational, occupational and self-employment opportunities. The present findings are in agreement with the studies conducted by Sharma et al. (2022); Chinchmalatpure and Tekale (2019).

Chi-square tests: Discipline-wise and gender-wise differences

Table 2 summarizes the chi-square test results for aspiration level differences across disciplines and gender.

H_{01} (no significant difference in aspiration levels across disciplines) was rejected for job aspirations ($\chi^2 = 8.74$, df = 3, p = .033) but retained for educational, self-employment, socio-economic, and economic aspirations. The significant discipline-wise difference in job aspirations indicates that students' career orientation toward employment is meaningfully shaped by the specific professional norms and labour market prospects of their disciplines most notably the structured job pathways (government veterinary officer, fisheries extension officer, agricultural engineer with NABARD or state agriculture departments) that vary markedly across these fields. The non-significant discipline effect on economic aspirations (p = .061) suggests that financial motivation is relatively homogeneous across disciplines, a finding that challenges simple narratives about 'more marketable' disciplines generating proportionally higher income aspirations.

H_{02} (no significant difference in aspiration levels between male and female students) was rejected for educational aspirations ($\chi^2 = 4.62$, df = 1, p = .032) and socio-economic aspirations ($\chi^2 = 6.15$, df = 2, p = .046), but retained for self-employment aspirations (p = .256). Female students displayed higher educational aspirations (65% versus 52% in the medium-to-high combined range), possibly reflecting sociocultural patterns in which higher education is perceived as a primary pathway to social mobility for women (Reddy & Rani, 2020; Meinam et al., 2023). Male students showed stronger socio-economic aspirations in some respects but female students were more likely to prioritize social recognition — a finding requiring more nuanced instruments in future research. The absence of a significant gender difference in self-employment aspirations is consistent with Mishra et al. (2021) and suggests that entrepreneurial motivation is not gender-differentiated among farm science undergraduates at this institution, contrary to general rural entrepreneurship literature.

Discipline-wise variation in aspirations of farm science students

The heat map of aspirations across discipline (Figure 2) depicts the various degrees of aspirations among students in four disciplines agriculture, veterinary, fishery and agri-engineering using six aspiration categories. The category of government career aspirations has the highest aspiration levels overall, with 70% of students expressing the greatest interest in fishery, closely followed by veterinary (68%), agriculture (65%) and agri-engineering (65%). This suggests that students across all subject areas strongly favour steady work in the public sector. Both socioeconomic recognition and high income (economic desire) are consistently high across all sectors, often between 60 and 65%, suggesting that students prioritize social standing and financial security. However, across all groups, agricultural science students had the lowest educational expectations, at 35%, which suggests a lack of enthusiasm in going to college. The moderate range of aspirations includes both self-employment and private or corporate employment, with private employment being marginally more desired than self-employment (Patel & Chauhan, 2023). Rather than being motivated by financial objectives, social recognition, and job stability, this general trend shows that students. The result aligns with the findings of Vinodkumar and Seema (2021).

Gender-wise distribution of aspirations among farm science students

The aspiration levels of male and female students are compared in six areas in the Heatmap of Aspirations (Figure 3) by Gender educational aspiration, job aspiration (government), private/ corporate jobs, self-employment, socio-economic (social recognition), and economic (high income). According to the heatmap, female students are more interested in pursuing higher education than male students, with females having a considerably higher level of educational aspiration (65%) than males (52%). There is a shared preference for working in the public sector, as seen by the virtually equal interest shown by both sexes in government positions (68% for male and 69% for female). It's interesting to note that male students are more likely than female students to prefer private or corporate employment (58%) and to be interested in working for own (33% vs. 28%). On the other hand, women are more likely

Table 2. Chi-square Tests of Aspiration Level Differences by Discipline and Gender

Aspiration Domain	Groups Compared	χ^2	df	N	p-value	Significance
Educational Aspirations	Gender (Male vs. Female)	4.62	1	160	.032	Significant*
Job Aspirations	Discipline (4 groups)	8.74	3	160	.033	Significant*
Self-employment Aspirations	Gender (Male vs. Female)	1.29	1	160	.256	Not Significant
Socio-economic Aspirations	Gender (Male vs. Female)	6.15	2	160	.046	Significant*
Economic Aspirations	Discipline (4 groups)	7.38	3	160	.061	Not Significant (trend)

* $p < .05$.

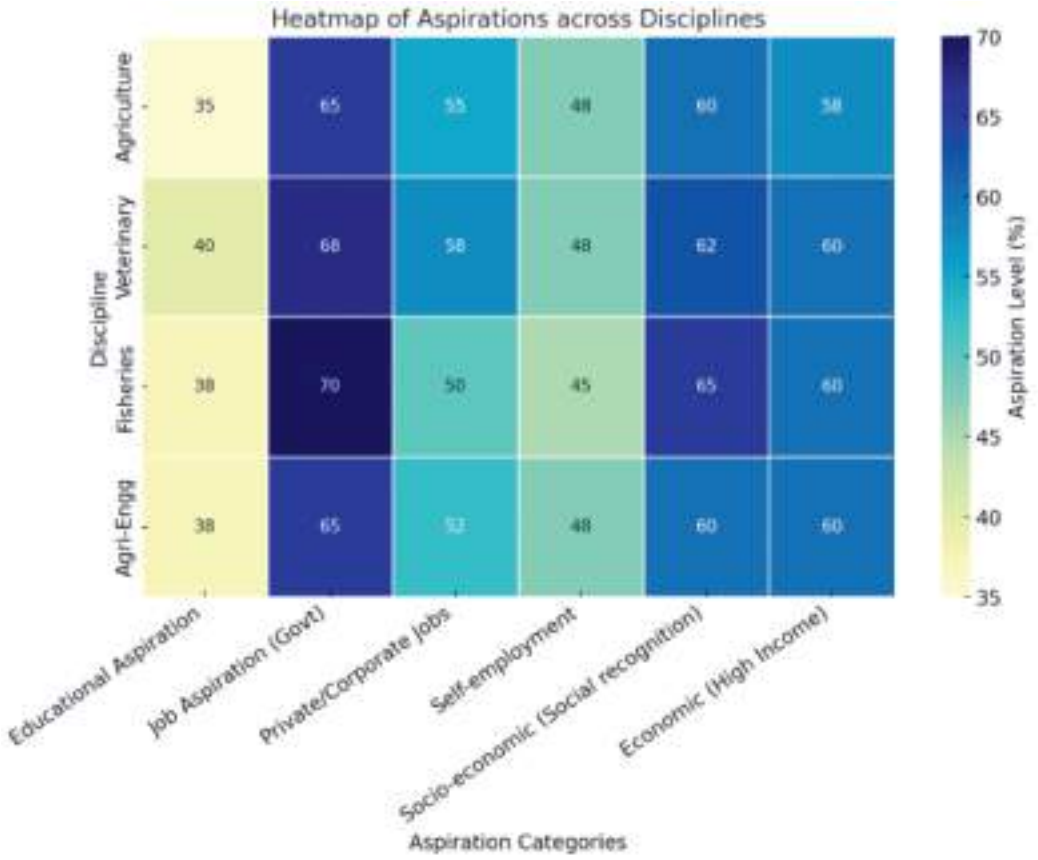


Figure 2. Heat map of Aspirations across Disciplines

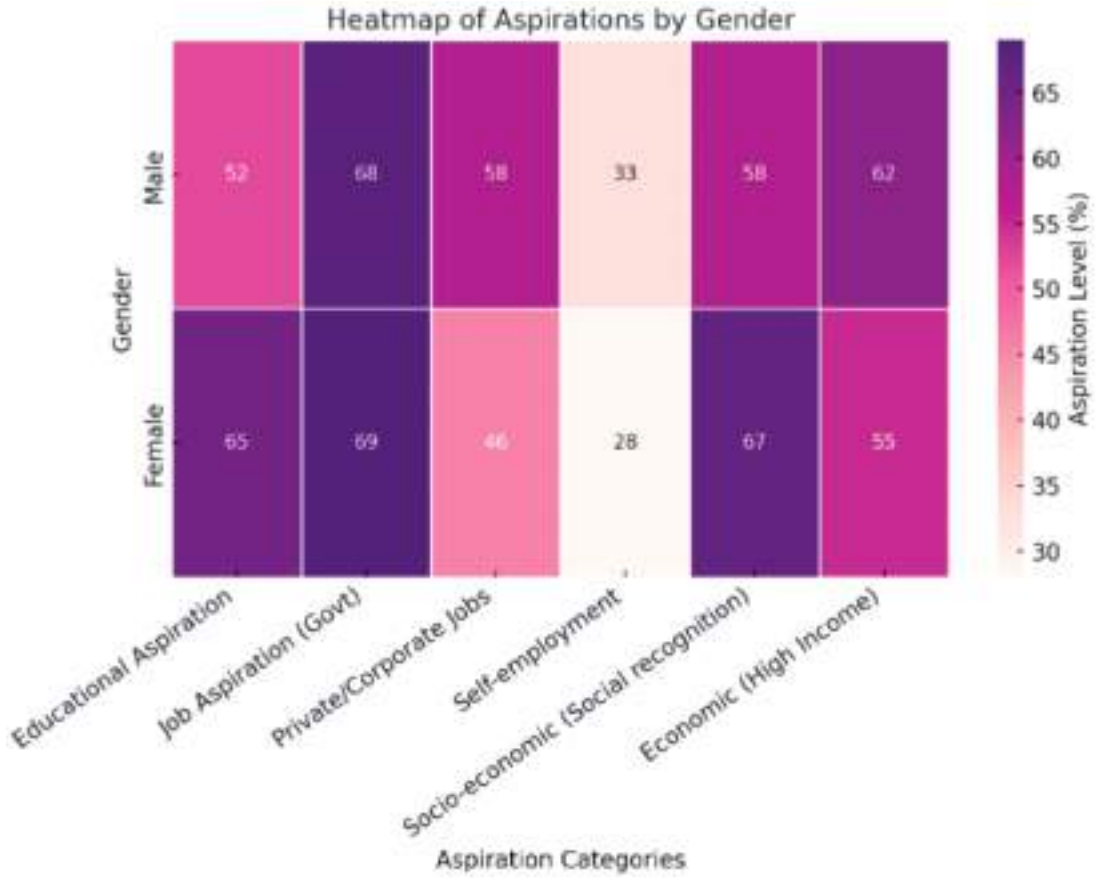


Figure 3. Heat map of Aspirations by Gender

than men to have socioeconomic aspirations (67%) compared to 58%, indicating that women are more driven to achieve social status and recognition. Finally, men are more likely than women to have high income aspirations (62% vs. 55%). Overall, the research indicates that while both sexes value job security and recognition, women are more focused on academics and social interactions, while males are more interested in financial gain and entrepreneurial pathways (Reddy & Rani, 2020).

DISCUSSION

The predominance of medium aspiration levels across all five domains and all four disciplines at CUTM is consistent with Aspiration Theory's prediction that aspirations converge around perceived social and institutional feasibility (Genicot & Ray, 2020). Students appear to set aspirations that reflect an awareness of both their potential and the structural constraints they face including limited postgraduate seats, competitive government recruitment, and perceived risk in self-employment. This moderation in aspiration, while adaptive in the short term, may constrain the agricultural sector's need for highly motivated graduates willing to pursue advanced research, technology entrepreneurship, or agri-business leadership. The comparatively higher aspiration profile of veterinary science students particularly in educational and socio-economic dimensions likely reflects the structured professional identity of veterinary medicine (licensing, service obligation, high public regard) that functions as an institutional 'aspiration anchor.' By contrast, the elevated low-category proportion in educational aspirations among agricultural engineering students suggests a vocational disengagement from further academic study that may be partly functional (given strong industry demand at the B.Tech level) but risks limiting long-term research capacity in the sector.

Gender differences in educational and socio-economic aspirations are consistent with sociological literature on gendered career socialization in India. Female students' stronger educational aspirations may reflect both the perceived protective value of higher credentials in the face of gender-based employment discrimination and the influence of institutional environments that actively encourage female academic achievement. Male students' marginally stronger self-employment and economic aspirations (not statistically significant) accord with Raju and Devarani (2023), who link entrepreneurial aspirations in farm science to masculine norms around financial independence a pattern that is shifting as agri-business becomes increasingly gender-inclusive (Agarwal & Saini, 2021).

The non-significant association between gender and self-employment aspirations ($p = .256$) is a substantively important null result: it suggests that targeted agri-entrepreneurship programmes need not be designed along strictly gendered lines, but rather should focus on discipline-specific barriers and institutional support structures. The trend-level economic aspiration difference across disciplines ($p = .061$) warrants replication with larger, multi-institutional samples before conclusions are drawn.

CONCLUSION

The findings carry specific, actionable implications. First, agricultural universities should incorporate structured career counselling from the second year of undergraduate study, with discipline-tailored modules that systematically expose students to the full range of career pathways including agribusiness, research institutions, and international agencies contexts likely to shift aspirations upward toward the high category. Second, agri-entrepreneurship incubation cells with seed funding and mentorship should be established, with a focus on agricultural engineering and agriculture students who show relatively higher low-category proportions. Third, the significant gender gap in educational aspirations calls for targeted scholarship and postgraduate fellowship programmes for female farm science graduates. Fourth, policy planners should recognize that income aspirations are broadly homogeneous across disciplines (consistent medium levels), implying that financial incentives alone will not differentiate disciplinary career choices; non-monetary factors such as social recognition, job security, and contribution to community development are comparably or more important motivators.

DECLARATIONS

Ethics approval and informed consent: Throughout the study, the respondents were asked for their informed consent.

Conflict of interest: The research was carried out without any financial or commercial ties that might be seen as a potential conflict of interest, according to the authors. The authors affirm that they carefully examined, amended and edited the content as necessary when preparing this work. The final content of this publication is entirely the authors' responsibility.

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Research Article

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Determinants of Farmers' Knowledge and Safe Pesticide Utilisation Behaviour: Artificial Neural Network Approach

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HIGHLIGHTS

- Socioeconomic, informational and perceptual factors have a major impact on farmers' knowledge and safe pesticide use practices.
- There is a clear knowledge-practice gap whereby information about safe pesticide use does not necessarily result in safe behaviour.
- Promoting safe pesticide use practices is greatly aided by extension services, media coverage and training initiatives.
- Artificial Neural Networks (ANNs) analysis successfully captured non-linear interactions and determined the relative significance of influencing factors.

ARTICLE INFO

Keywords: Artificial neural network, Extension services, Knowledge level, Pesticide utilisation behaviour, Safe pesticide practices, Socio-economic factors.

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ABSTRACT

Pesticides are increasingly being used to enhance agricultural productivity, but the risks of unsafe pesticide application to both human health and the environment can be severe. In this study, Artificial Neural Network (ANN) analysis along with traditional statistical techniques were used to analyze factors influencing farmers knowledge and pesticide use behaviour. The study was carried out in 2025-26 in Kakinada district of Andhra Pradesh, utilizing ex-post facto research design. A sample of 240 farmers were selected by means of multistage random sampling. Information was collected with the help of a well-structured and pre-tested interview schedule. Correlation and multiple regression analysis were used to determine the association of socio-economic, communication and behaviour variables with farmers knowledge and use behaviour. ANN model was developed to determine non-linear relationship and variable importance. The results clearly indicated that, education, extension contact, mass media exposure and risk orientation had significant role in farmer knowledge and pesticide use behaviour. From ANN, mass media exposure was most influential independent variable followed by risk orientation and social participation that implies the communication-based extension efforts are the right way to disseminate the safe pesticide application techniques for intensive pesticide use production systems.

INTRODUCTION

Pesticides have an important place in modern agriculture in enhancing productivity, protecting crop from disease and pests and contributing to food security in the developing countries like India (Bhandari et al., 2018). However, improper and unsafe use of pesticides has generated serious environmental pollution, loss of bio-diversity and unfavourable health impact on the farming population (Damalas & Koutroubas, 2016). Majority of the farming communities have strong dependency on the use of chemical

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pesticides as production challenges mount up to prevent the losses and farmers have no enough knowledge on safe storage, usage and disposal of the pesticides, posing great occupational health risks along with environmental pollution and chronic health hazards in the rural areas (Thorat et al., 2023; Yaseen et al., 2024).

The use behaviour and the knowledge among the farmers regarding pesticide are one of the most important determining factors for safe and sustainable use of pesticides. Factors influencing farmers' use behaviour and their decision-making behaviour towards pesticides include many socio-economic factors (e.g., level of education, extension services, communication exposure, social participation) and behaviour-related factors (e.g., knowledge, risk perception) (Naghavi et al., 2024). Many of the farmers possess the knowledge about negative effects on human health and the environment due to pesticide use, but are not utilizing them into their behaviours and a significant knowledge-practice gap exists among the farmers (Sai et al., 2019). Farmers generally use the information gained through informal sources like the local dealers and other fellow farmers that possibly induce unsafe practices for the increased use of pesticides (Okoffo et al., 2016). Other attitudes, perceived use utility and behavioural intention affect usage of safety equipment, as well as method of disposal of pesticides (Kaur et al., 2022). Perceived occupational dangers, training exposure and awareness levels all have a significant impact on farmers' pesticide handling behaviours and safety procedures (Jallow et al., 2017).

In earlier studies pesticide knowledge and behaviour have been analyzed by the use of ordinary statistical methods such as correlation and regression analysis in order to find relation among socio-economic parameters with behavioural patterns of the farmers (Choudhary et al., 2022). These studies offer significant information, but failed to account for and represent the multiple and non-linear interactions among behavioural, perceptual and communicative variables, which affects behaviour related to the pesticide application. The application of artificial neural network models in analyzing multi-dimensional behavioural relationships has emerged recently in agricultural research due to their abilities in exploring the non-linear underlying patterns and relationship between the variables which is better than traditional linear models (Liakos et al., 2018). There are few researches done on pesticide knowledge and utilization behaviour by farmers using ANN approach, and this has not yet been explored in Andhra Pradesh, especially in Kakinada district, which also involves a lot of pesticides. The objective of this research was to examine the factors affecting farmers' level of knowledge and behaviour in relation to pesticide use through ANN analysis and to ascertain the relative significance of the socio-economic, communication and behavioural variables on the safe pesticide usage behaviour.

METHODOLOGY

The present study was carried out in Kakinada district of Andhra Pradesh during the year 2025-2026 since the district was having tremendous horticultural activities and the farmers use the pesticides widely. For the selection of the respondents, multistage sampling technique was used. In the first stage eight mandals were purposively selected basing on the maximum area where vegetables are grown. In the second stage, three villages were randomly selected from each mandal in the selected mandals, i.e., twenty-four villages in total. In the last stage, 10 farmers were randomly selected from each of the selected villages, thus giving 240 respondents in total.

An organised, pre-tested interview schedule was used to collect data. A two-point continuum (Yes = 2 and No = 1) is used for knowledge level. Previous approaches for evaluating farmers' agricultural and environmental knowledge levels served as a foundation for the development and standardisation of knowledge measuring processes (Sharma, 2023). A three-point continuum (Always = 3, Sometimes = 2, Never = 1) is used to quantify utilisation behaviour. The relationships between independent and dependent variables were studied through correlation analysis and the contribution of individual independent variable to the farmers' knowledge and use of pesticides was measured through multiple regression analysis.

Artificial Neural Network (ANN) modelling and suitable statistical methods were used to examine the gathered data. ANN is a computer model built using the ANN technique that draws inspiration from the architecture and operations of biological neural networks (Gupta & Raza, 2019). Because ANN models can examine multidimensional interactions among variables and increase prediction efficiency in complicated farming systems, they have recently become more significant in agricultural behavioural studies (Pradhan et al., 2025). Correlation and regression analyses were used to detect relations between variables, whereas ANN was used to capture complex non-linear interactions and determine the relative relevance of influencing elements.

The study took into consideration two sets of variables: two dependent variables (Y) and ten independent variables (X) that represented socioeconomic and communicative factors.

$X = x_1, x_2, x_3, \ldots\ldots\ldots x_9$ and $Y = y_1, y_2$

x_1 = age, x_2 = education, x_3 = experience, x_4 = no. of crops, x_5 = annual income, x_6 = total landholding, x_7 = access to extension services, x_8 = social participation, x_9 = risk orientation, x_{10} = mass media exposure, y_1 = knowledge level towards pesticides, y_2 = utilisation behaviour of pesticides

Two sets of variables were considered for the study: ten independent variables (X) representing socio-economic and communication characteristics and two dependent variables (Y). An input layer with ten independent variables, a hidden layer with seven neurones using a hyperbolic tangent activation function and an output layer with two dependent variables using an identity function made up the Artificial Neural Network model.

RESULTS

Correlation co-efficient (r) of independent variables and dependent variables

In Table 1, the correlation analysis revealed that education, extension contact, mass media exposure, social participation and risk orientation are positively and significantly related to farmers' knowledge and pesticide utilisation behaviour, but age was negatively related and means that older farmers were less responsive to adopt improved pesticide practices. The results shows that information and communication related variables are significantly related to farmers' adoption behaviour of improved pesticide practices.

Table 1. Correlation co-efficient (r) of independent variables and dependent variables

Variables	Knowledge level towards pesticides	Utilisation Behaviour of pesticides
Age	-.644**	-.641**
Education	.703**	.608**
Experience	.774**	.801**
No. of crops	0.004	0.030
Annual Income	.843**	.864**
Total landholding	.805**	.793**
Access to Extension Services	.816**	.804**
Social Participation	.723**	.784**
Risk Orientation	.878**	.923**
Mass Media Exposure	.869**	.893**
Knowledge Level	1	.941**
Utilisation Behaviour	.941**	1

*Significant at 5% ** Significant at 1%

Multiple linear regression analysis of independent variables with both dependent variables

The multiple linear regression analysis in Table 2 shows that the identified independent factors account for 87.7% of the variance in farmers' knowledge level (R = 0.877) and 91.7% of the variance in farmers' use of pesticides (R = 0.917). While beta values (standardised coefficients) indicate the degree to which one variable can influence the dependent variable in relation to the others, B values (unstandardised coefficients) display the actual change in dependent variables for each unit change in the independent variable. While mass media exposure (= 0.433), access to extension services (= 0.173) and risk orientation (= 0.143) have the greatest influence on pesticide utilisation behaviour, access to extension services (= 0.351) and exposure to the media (= 0.230) had a favourable impact on knowledge level. Sig. values indicate statistical significance, while T values indicate the strength of each variable's contribution. The variable significantly affects the dependent variable when the values are less than 0.05. The independent variables used in the study did not indicate substantial multicollinearity, according to the VIF values, which ranged from 1.844 to 7.463. The fact that variables like mass media exposure (7.463), risk orientation (7.215) and access to extension services (7.010) displayed relatively higher VIF values but stayed within the acceptable limit confirmed the statistical reliability of the regression and ANN models for analysing farmers' knowledge level and pesticide usage behaviour.

Neural network architecture for farmers knowledge level and utilisation behaviour of pesticides

Figure 1 ANN model successfully incorporated all 10 independent factors through a hidden neural layer to predict the two dependent variables, farmers' knowledge level and pesticide usage behaviour. The chart shows that, in comparison to structural farm variables, communication and behavioural variables had a greater impact on the outputs. Risk orientation also showed strong correlations with knowledge (r = 0.878) and utilisation behaviour (r = 0.923), while mass media exposure demonstrated a very high

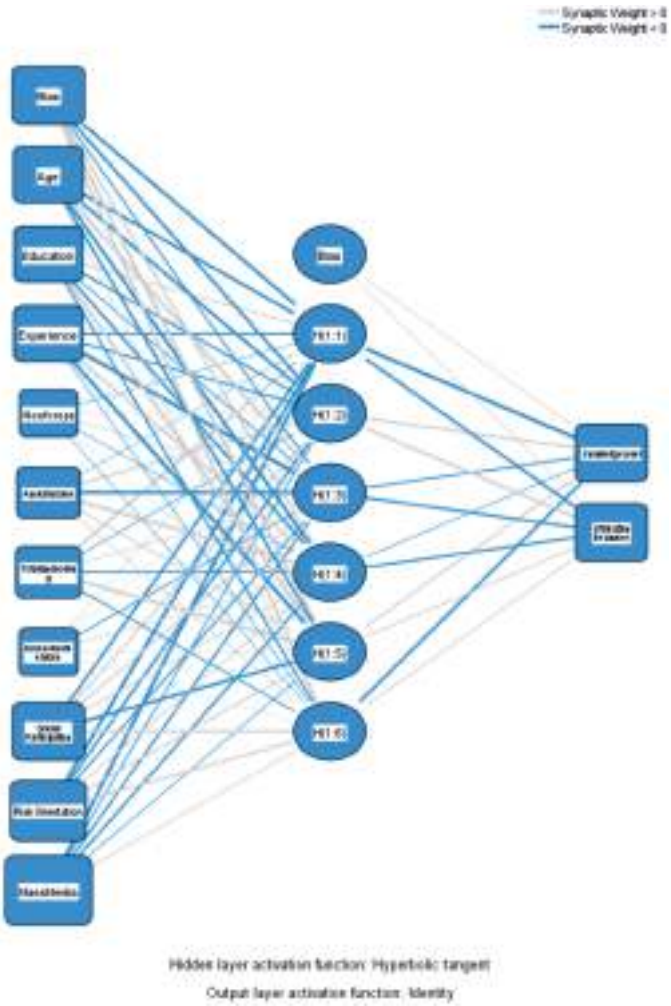


Figure 1. Developed neural network architecture for farmers knowledge level and utilisation behaviour of pesticides

positive correlation with knowledge level (r = 0.869) and utilisation behaviour (r = 0.893). These findings provide strong support for this. Mass media exposure had the highest standardised beta value for pesticide use behaviour in the regression model (β = 0.433), followed by risk orientation (β = 0.143) and access to extension services (β = 0.173), suggesting that these factors had a stronger influence on behavioural outcomes within the ANN architecture. Therefore, the ANN figure confirms that communication exposure, behavioural orientation, and institutional support systems all interacted to influence farmers' pesticide behaviour through interconnected neurones rather than a single element acting alone.

The high R^2 values for knowledge level (0.877) and pesticide usage behaviour (0.917) in Figure 1 ANN architecture also demonstrate the model's outstanding predictive capabilities. The model was able to capture intricate non-linear interactions that traditional regression was unable to adequately explain thanks to the hidden layer's 10 neurones and hyperbolic tangent activation function. The ANN structure shows that even smaller contributing variables interacted with stronger predictors to influence behavioural outcomes collectively, despite the fact that variables like annual income, number of crops, and landholding showed weaker regression contributions. The independent variable important results are further

Table 2. Multiple Linear Regression analysis of independent variables with both dependent variables

Variables	Knowledge level towards Pesticides (R^2 =0.877)					Pesticide Utilisation Behaviour (R^2 =0.917)					Collinearity Statistics
	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	VIF
	B	Std. Error	Beta			B	Std. Error	Beta			
Age	23.192	2.510		9.240	0.000	6.994	1.799		3.888	0.000	2.789
Education	-1.207	0.576	-0.081	-2.096	0.037	-1.050	0.413	-0.081	-2.546	0.012	3.624
Experience	0.451	0.232	0.086	1.942	0.053	-0.544	0.167	-0.119	-3.267	0.001	4.721
No. of Crops	-0.821	0.448	-0.092	-1.830	0.069	-0.725	0.321	-0.093	-2.256	0.025	1.913
Annual Income	-0.039	0.146	-0.009	-0.266	0.791	-0.035	0.105	-0.009	-0.331	0.741	1.844
Total landholding	0.349	0.194	0.057	1.804	0.073	0.172	0.139	0.032	1.241	0.216	3.810
Access to Extension Services	2.977	0.383	0.351	7.768	0.000	1.274	0.275	0.173	4.637	0.000	7.010
Social Participation	-0.034	0.130	-0.016	-0.262	0.794	-0.010	0.093	-0.006	-0.111	0.911	3.046
Risk Orientation	0.453	0.427	0.043	1.061	0.290	1.313	0.306	0.143	4.294	0.000	7.215
Mass Media Exposure	0.210	0.057	0.230	3.698	0.000	0.343	0.041	0.433	8.449	0.000	7.463

supported by the figure, which shows that mass media exposure had the highest importance value of 0.26 (100% normalised importance), followed by risk orientation (0.16; 61%) and social participation (0.13; 49%). Therefore, the ANN figure verifies that behavioural traits and communication-based variables were the main factors impacting vegetable producers' awareness of and use of safe pesticides in the research area.

Independent variable importance

According to Figure 2, mass media was the most influential variable, with an important value of 0.26 (100% normalised importance). This suggests that media exposure, including television, radio, newspapers and the internet, had a significant impact on the dependent variable's extent. Risk orientation has an importance score of 0.16 (61% normalised importance), making it the second most influential variable. It suggests that those who take a lot of risks are more influential. Social Participation ranked third with an importance value of 0.13 (49% normalised relevance). It suggests that individuals who participate in social organisations and other social activities at a high level have a favourable influence on the dependent variable. The moderate contributing variables include age (0.11; 42%), experience (0.10; 40%) and education (0.10; 39%), suggesting that individuals with high levels of age, experience and education are comparatively higher influencing variables. With an importance value of 0.06 (26%) for total landholding and 0.05 (20%) for annual income, these factors were shown to have lower influencing power on the model. Access to extension services (0.01; 4%) and the number of crops (0.007; 2%) were two of the extremely

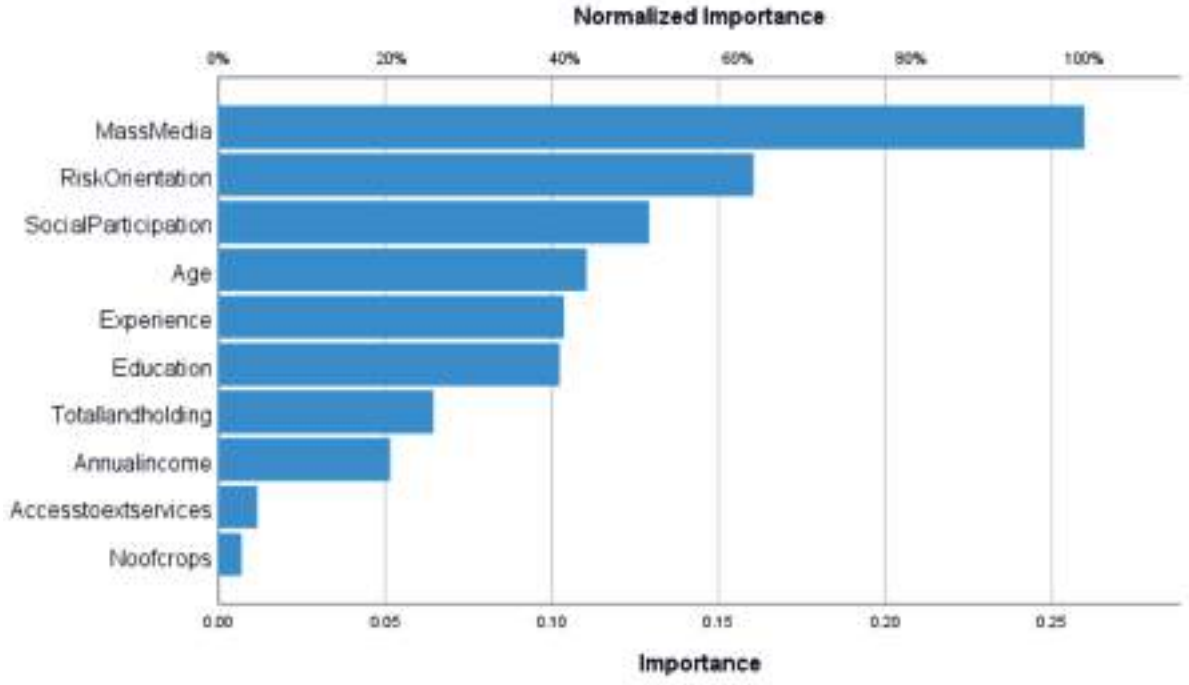


Figure 2. Independent Variable Importance

Table 3. Neural Network Information Summary

Neural Network Information Summary				
A.	Input Layer	Covariates	1	Age
			2	Education
			3	Experience
			4	No. of crops
			5	Annual income
			6	Total landholding
			7	Access to extension services
			8	Social Participation
			9	Risk Orientation
			10	Mass Media Exposure
		Number of Units[a]		10
		Rescaling Method for Covariates		Standardized
B.	Hidden Layer(s)	Number of Hidden Layers		1
		Number of Units in Hidden Layer 1[a]		10
		Activation Function		Hyperbolic tangent
C.	Output Layer	Dependent Variables	Knowledge Level	Knowledge Level
			Utilisation Behaviour	Utilisation Behaviour
		Number of Units		2
		Rescaling Method for Scale Dependents		Standardized
		Activation Function	Identity	
		Error Function	Sum of Squares	

low influencing variables since they had very little bearing on the dependent variable. Overall, it was discovered that behavioural traits and communication variables were more significant than economic and other farm-related variables.

Neural network information summary

According to Table 3, the ANN had two dependent variables farmers' knowledge and their use of pesticides and ten input variables. The intricate relationships between socioeconomic, informational and behavioural aspects were captured by a single hidden layer consisting of ten nodes. The ANN technique successfully investigated these connections between farmers' behavioural dimensions and their socioeconomic traits, informational and behavioural features, where risk orientation, education, extension contacts and the media all contributed to a better understanding of farmers' behaviours. Additionally, it demonstrated that the ANN method could accurately simulate relationships between factors to comprehend farmers' pesticide application practices. ANN is a useful model to explain the interactive nature of relationships between various determinants in farmers' knowledge and safety of pesticide application, as the results demonstrated that communication and information variables have a stronger impact in predicting the behavioural outcomes than structural farm characteristics.

Table 4. Comparative Performance of Regression and ANN Models

Parameter	Regression Model	ANN Model
R^2 (Knowledge Level)	0.877	Higher
R^2 (Utilisation Behaviour)	0.917	Higher
Prediction Accuracy	Moderate	High
Capability to capture non-linear effects	Limited	Strong
Variable interaction modelling	Weak	Strong

Comparison between regression and ANN models

Table 4 demonstrates that the ANN model performed better than the regression model in forecasting farmers' knowledge level and pesticide use patterns. Regression analysis yielded good R^2 values (0.877 for knowledge level and 0.917 for utilisation behaviour), however ANN showed better prediction efficiency with values and higher accuracy. Although regression analysis was useful for finding direct correlations between variables, it was not very good at capturing intricate behavioural interactions. ANN, on the other hand, was able to identify nonlinear and interrelated effects among behavioural, socioeconomic and communication variables, leading to a greater capacity for prediction. The results thus validate that, in comparison to traditional regression analysis, ANN offers a more dependable and thorough knowledge of farmers' behavioural responses regarding pesticide use.

DISCUSSION

The discussion shows that rather than being influenced by a single independent factor, farmers' awareness of and use of pesticides are influenced by interrelated informational, socioeconomic and perceptual elements. Respondents' knowledge of pesticide application techniques and safety precautions was moderate, but it did not always convert into safe usage practices. Vegetable producers use of agricultural information is greatly influenced by their access to trustworthy information sources and extension contacts, suggesting that knowledge alone cannot guarantee behavioural adoption in the absence of effective communication mechanisms (Choudhary et al., 2022). Previous research has also shown that farmers continue to handle pesticides hazardously and apply them excessively even when they are aware of the negative

effects since their knowledge of these risks is still incomplete (Gupta et al., 2010).

These conclusions were reinforced by the ANN analysis, which found latent non-linear correlations between behavioural orientation, institutional support systems and communication exposure. In contrast to regression models, ANN successfully captured threshold effects and the combined influence of variables influencing the behaviour of pesticide use. Mass media exposure was found to be the most significant predictor in the ANN significance analysis, followed by risk orientation and social engagement. This indicates that communication and perception-oriented variables have a greater influence on behavioural adaptability than economic parameters. Attitudes, beliefs and perceived utility have a significant impact on their behavioural choices regarding pesticide safety procedures and usage habits (Kaur et al., 2022). The adoption of safe pesticide handling procedures is strongly influenced by vegetable growers' perceptions regarding pesticide safety measures (Singh et al., 2025). Despite being aware of the risks involved, farmers frequently prioritise crop protection and financial benefits, which leads to overuse or misuse of pesticides.

ANN showed that farmer's impact increased when they interacted with behavioural orientation and communication exposure factors. Extension programs that include demonstrations and tailored advisories significantly improve farmers' capacity to make decisions and promote safer pesticide use practices (Saha et al., 2024). Behavioural adaptation was also greatly influenced by socioeconomic factors like education and access to information sources. Farmers' attitudes and actions regarding agricultural technologies and safety procedures are significantly influenced by socioeconomic circumstances and information accessibility (Bharat et al., 2022). Media exposure, education and extension contact have a favourable impact on farmers' attitudinal orientation and knowledge development (Kumari et al., 2025).

Interactive and experiential learning strategies significantly enhance safe pesticide use practices. Farmer field schools and hands-on training programs increase farmers' proficiency with safe pesticide handling techniques (Davis et al., 2018). Despite knowledge of the hazards associated with pesticides, production pressure and a lack of training opportunities continue to promote improper pesticide usage (Paine et al., 2021). Farmers' learning retention and behavioural adaption are greatly enhanced by communication-based treatments such dramatised presentations and interactive extension activities (Sahar et al., 2020). Digital apps, mobile-based information systems and AI-enabled advisory platforms increase farmers' access to timely ideas and encourage their behavioural adoption (Kumar et al., 2025; Mittal et al., 2016). Social information networks and communication systems had a major impact on farmers' learning outcomes and behavioural adaptation (Ogheneakoke et al., 2025). Additionally, applications of ANN and machine learning techniques showed exceptional proficiency in the analysis of hidden variable interactions and multidimensional agricultural behavioural systems (Liakos et al., 2018; Suman et al., 2025). Through intelligent predictive frameworks, advanced AI-based modelling techniques have also shown great analytical potential in comprehending intricate behavioural and infrastructural systems (Sharma & Dehalwar, 2026).

CONCLUSION

This study discovered that farmers' use of pesticides is influenced not only by knowledge level but also by communication exposure, behaviour orientation and institutional support. Respondents' adoption of waste disposal, storage and safety precaution procedures was found to be low, despite their modest level of understanding of pesticide use. The results of the ANN analysis show that the variables mass media exposure, risk orientation and extension contact have non-linear relationships with behavioural outcomes. The findings suggest that extension services should prioritise behaviour adoption above information dissemination. Additionally, there is a need for hands-on training sessions that cover all aspects of safe handling, waste disposal and protective measures. Farmers' perceptions of risk would be improved by better extension services and media attention, which would encourage safe practices. According to several farmer groups, interventions are necessary to support environmentally sound agriculture.

DECLARATIONS

Ethical approval and informed consent: No ethical approval is needed for this study.

Conflict of interest: Authors have no conflict of interest.

Authors contribution: Pandiri Neha Pragnya: paper plan execution and manuscript preparation; Peddi Naga Harsha Vardhan and Vaishnavi Pulletikurthi: Monitoring, paper planning and manuscript editing; Ashok Kumar, Nihal R and Tumma Mounika: Monitoring, manuscript editing and manuscript correction.

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Research Article

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Fuzzy Cognitive Mapping in Natural Resource Management: A Global Bibliometric Analysis with India-Specific Insights (1995–2025)

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HIGHLIGHTS

- The field has grown from a niche method into a globally distributed research domain with an 11.75% annual growth rate and thematic focus has shifted from technical modelling toward participatory and climate applications.
- The method's strength lies in encoding expert knowledge without requiring quantitative precision.
- India's 23-document corpus, though small, matches the global citation average (23.7 vs. 22.74 citations per document).

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Keywords: Natural resource management, Participatory modelling, Fuzzy cognitive mapping, Bibliometric analysis, Keyword co-occurrence network, Thematic analysis, Decision support systems.

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ABSTRACT

Natural Resource Management (NRM) is a complex, multi-dimensional domain in which effective impact assessment demands tools capable of handling subjectivity, uncertainty and stakeholder diversity. Fuzzy Cognitive Mapping (FCM) has emerged as such a tool, enabling the integration of qualitative knowledge and stakeholder perspectives into structured causal models. This study presents a bibliometric analysis of Scopus-indexed documents applying FCM in NRM contexts from 1995 to 2025, examining global trends in publication output, leading countries, institutions, journals, and authors. Bibliometric and network visualisation analyses were performed using Biblioshiny (bibliometrix R package) and VOSviewer. Qualitative thematic analysis of India-specific documents was conducted to complement the quantitative findings. The field has grown at an annual rate of 11.75%, with the United States and Greece leading global output. India, though modest in publication volume, shows a dynamic trajectory, with studies spanning precision agriculture, climate change adaptation, conservation conflicts, and disaster resilience. Collectively, the findings highlight FCM's expanding role in applied, participatory, and sustainability-oriented NRM projects.

INTRODUCTION

The phrase "Natural Resource Management" (NRM) gained currency in the United States in the early 1960s, used interchangeably with "environmental management" and "resource management" (Miller et al., 2019). Against a backdrop of climate change, biodiversity loss, and mounting sustainability pressures, NRM research has gained growing attention (Nichols et al., 2011). Effective NRM practices can mitigate climate vulnerability, reduce disaster risk, and support biodiversity conservation (Abramovitz et al., 2001), and NRM is widely recognized as foundational to achieving the United Nations Sustainable Development Goals (Bansal et al., 2022).

However, impacts of NRM are notoriously difficult to assess. The biophysical effects of interventions are hard to quantify due to the intricate interplay of ecological, socio-economic, and

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institutional factors (Rahman, 2026). Impacts are frequently indirect and manifest over extended timescales, complicating attribution and measurement (Falk et al., 2021). Traditional impact assessment methods (Gupta et al., 2020; Gupta et al., 2021; Jha et al., 2025; Krishna et al., 2025) often fall short in capturing the subjective, qualitative, and interdependent characteristics of socio-ecological systems (Obiedat & Samarasinghe, 2022). This makes comprehensive impact assessment a continuing methodological challenge in NRM scholarship (Jain et al., 2025).

Fuzzy Cognitive Mapping (FCM) has emerged as a promising response to this challenge. FCM provides a structured yet flexible framework for incorporating diverse forms of knowledge and stakeholder perspectives into models of system dynamics (Gray et al., 2015; MacMillan et al., 2024). It captures causal relationships between system variables, assigns positive or negative weights to conceptual linkages, and supports "what-if" scenario analyses that can inform adaptive management and planning (Özesmi & Özesmi, 2004). Its capacity to encode expert knowledge without requiring full quantitative precision makes FCM particularly valuable in data-scarce, knowledge-rich contexts.

Despite decades of growing application, no comprehensive bibliometric analysis has examined the structure and global evolution of this literature, nor has its development in India been systematically assessed. India warrants dedicated attention for several reasons. It combines exceptional agrarian complexity, over 140 million farm holdings, the majority smallholder, with acute exposure to climate variability, water stress, and biodiversity pressures. This makes it a high-stakes test case for participatory, knowledge-based NRM tools. Yet India's FCM research has developed with limited visibility in the global conversation, and no study has mapped its trajectory, thematic contours, or connection to international networks. This gap limits evidence-based guidance for researchers and policymakers seeking to apply FCM in Indian NRM contexts. The present study addresses that gap by analysing Scopus-indexed FCM-in-NRM documents from 1995 to 2025, and supplements the bibliometric findings with qualitative thematic analysis of India-specific research.

METHODOLOGY

This study employs bibliometric analysis to examine the structure and development of FCM-related NRM literature (Anuranj & Vishnu, 2026; Donthu et al., 2021). The search was performed using a set of keywords related to fuzzy cognitive mapping (FCM) in natural resource management (NRM). Keywords included 'Fuzzy Cognitive Map', 'Agriculture', 'Livestock', 'Fish', 'Natural Resource', 'Soil', 'Water', 'Watershed', 'Technology Transfer', 'Transfer of Technology', 'Impact Assessment', 'Project Evaluation', 'Impact Pathway'.

The following query was applied to Scopus with time restriction (1995-2025):

(TITLE-ABS-KEY ("fuzzy cognitive mapping" OR "fuzzy cognitive maps") AND TITLE-ABS-KEY ("agriculture" OR "livestock" OR "fish" OR "natural resource" OR "soil" OR "water" OR "watershed" OR "technology transfer" OR "transfer of technology") OR TITLE-ABS-KEY ("impact assessment" OR "project evaluation" OR "impact pathway")

Scopus was selected as the primary database given its standing as a curated, high-quality bibliometric source with broad coverage of peer-reviewed literature across disciplines (Baas et al., 2020). The query uses Boolean AND to require both an FCM term and an NRM-domain term, while OR groups synonyms within each category; impact-related terms are added via a separate OR clause to capture evaluation-focused studies. Inclusion criteria restricted results to peer-reviewed research articles, reviews, and conference papers published in English between 1995 and 2025. Non-English documents, editorials, book chapters, and errata were excluded. Search results were downloaded in .bib and .csv formats. After removing duplicate records and screening for relevance. The final dataset comprised 305 scholarly publications. Bibliometric and visualization analyses were performed using Biblioshiny, the web-based interface of the bibliometrix R package (Aria & Cuccurullo, 2017) and VOSviewer (version 1.6.19) software (Centre for Science and Technology Studies, Leiden University, Leiden, The Netherlands). Qualitative thematic analysis of India-specific abstracts was conducted to identify patterns of FCM application (Krithika et al., 2023).

RESULTS

Descriptive overview and publication trends

Between 1995 and 2025, 305 documents on FCM in NRM appeared across 211 sources at an annual growth rate of 11.75%. The average document age of 7.61 years reflects a young but steadily maturing field, and an average of 22.74 citations per document signals strong academic impact. Collaboration was extensive, with the average paper involved more than four authors, with 39.02% of documents featuring international co-authorship. Journal articles (76%) and conference papers (15%) dominate document types.

For India, 23 documents spanning 22 sources were identified, covering 2015–2025, with an annual growth rate of 5.24%, covering 2015–2025, with an annual growth rate of 5.24% which is lower than the global 11.75%, reflecting India's later entry into the field (first publication in 2015 versus 1995 globally). Indian papers averaged 23.7 citations, closely approximating the global figure, and featured comparable levels of collaborative authorship

Table 1. Descriptive bibliometric overview of FCM-in-NRM literature: global (1995–2025) and India (2015–2025)

Metric	Global (1995–2025)	India (2015–2025)
Sources (journals, books, etc.)	211	22
Documents	305	23
Annual growth rate (%)	11.75	5.24
Document average age (years)	7.61	6.13
Average citations per document	22.74	23.7
References	2526	204
Authors' Keywords (DE)	977	92
Authors	1,030	73
Co-authors per document	4.36	4
International co-authorship (%)	39.02	34.78
Articles/Reviews/Conference papers	244/2/48	20/1/—

(approximately 4 per paper) and international co-authorship (34.78%). The descriptive overview is summarised in Table 1.

Bibliometric analysis tracked the evolution and dynamics of research themes over time. Globally, FCM-based NRM research started with technical foundations like fuzzy sets, knowledge representation, and basic decision-support tools, roughly between 2004 and 2012. By the mid-2010s, attention moved toward complex systems modelling, participatory planning, and decision support. From 2020 onward, the field concentrated on environmental protection, ecosystem services, food security, and conservation, with climate change, land use dynamics, and sustainable resource systems becoming recurring concerns (Figure 1). In India, FCM studies began with a technical emphasis between 2016 and 2018. By 2021, research had expanded toward stakeholder engagement and local contexts. Subsequently, studies turned toward human-dimensions questions like perceptions, decision pathways, and impact assessment, reflecting a broader shift toward applied, people-centred NRM inquiry (elaborated later in Table 2).

Mapping the global research landscape: countries, institutions, and journals

The United States leads global output with 146 publications (Figure 2), a dominance consistent with its large-scale federal funding ecosystem for environmental and agricultural research. Greece ranks second, its disproportionately high output driven by concentrated research groups in computational intelligence and FCM methodology. China, United Kingdom, Canada, Australia, India, Netherlands, Spain, and Turkey complete the top ten, suggesting that FCM-NRM research has diffused well beyond its Euro-American origins.

Wageningen University and Research (Netherlands) lead institutional output with 20 publications, followed by Universidad Politécnica de Madrid (Spain, 17), Michigan State University (USA) and the University of Thessaly (Greece), each contributing 14 publications. Institutions from Italy, Australia, and India also feature prominently. In India, Sri Sivasubramaniya Nadar (SSN) College of Engineering leads with 6 FCM-related publications in NRM domains, followed by the Institute of Rural Management Anand (IRMA). That a single engineering college dominates India's output points to a narrow institutional base, whereas global production is distributed across agricultural, environmental, and engineering departments (Figures 3a, 3b). (Figures 3a, 3b).

Citation count is a widely used indicator of a source's relevance and impact within a research field (Bornmann & Daniel, 2008; Barman et al., 2026). The *Journal of Environmental Management* leads with 10 publications, followed by *Ecology and Society* (8) and *Sustainability (Switzerland)* (7). In India, 22 sources reflect interdisciplinary breadth. Chemosphere leads with 2 articles; *Agricultural Systems*, *Climatic Change*, and *Global Environmental Change* each feature one publication, spanning agriculture, ecology, engineering and applied mathematics (Figures 4a, 4b).

Intellectual foundations: influential authors and cited works

Author publication count is a standard bibliometric measure of scholarly productivity in each domain (Donthu et al., 2021). Globally, E.I. Papageorgiou leads with 16 articles, followed by S.A. Gray (13) and R. Giordano (10). Several other authors like Kok K, Kokkinos K, Anokhina MY, Arvanitis KG, Groot JCJ, Kyriakarakos G, and Papadakis G had contributed 5 to 6 documents, indicating a moderately concentrated but growing author base. The presence of multiple Greek-affiliated researchers among the top contributors aligned with Greece's strong standing in global FCM-NRM output. In India, H. Chudasama, E.I. Papageorgiou, P.K. Singh, and L.S. Subramanian each contributed 3 publications which is a modest count compared with the global leaders, but notable given India's shorter publication window (2015–2025 versus 1995–2025). Arthi K, Goswami R, Mainuddin M, Malarkodi KP, Poomagal S, and Ray K had contributed two articles, indicating that Indian FCM-NRM research, while growing, remained distributed across a relatively small and emerging author community (Figures 5a, 5b).

Citation frequency is a standard indicator of a document's influence within a given field (Garfield, 1955, 1972). Globally,

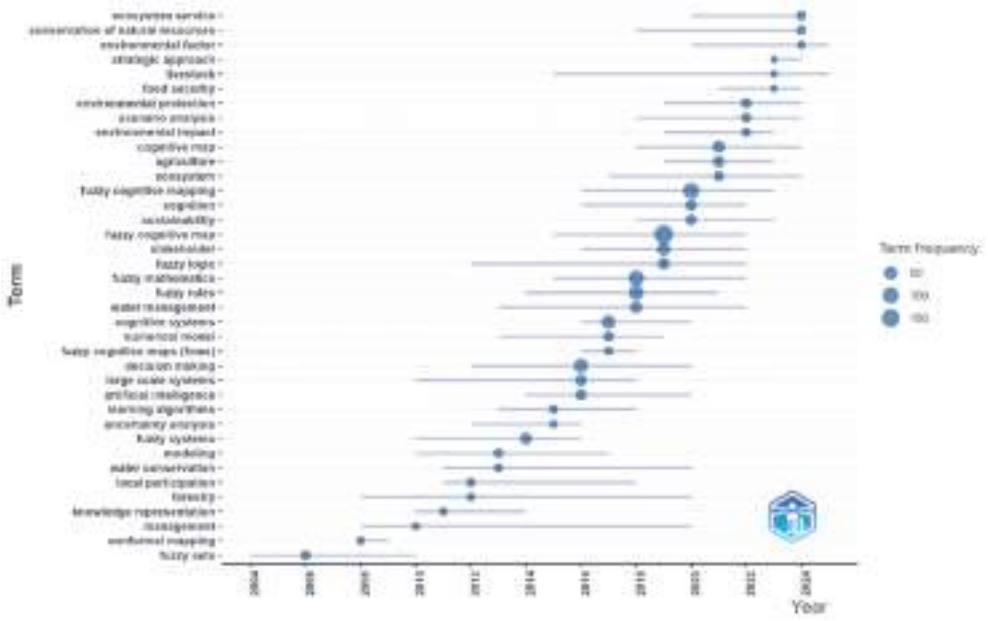


Figure 1. Temporal evolution of trending research topics in FCM-NRM literature, 1995–2025. Emerging topics appear in the upper right quadrant of the figure, and the size of the circles represents their term frequency.

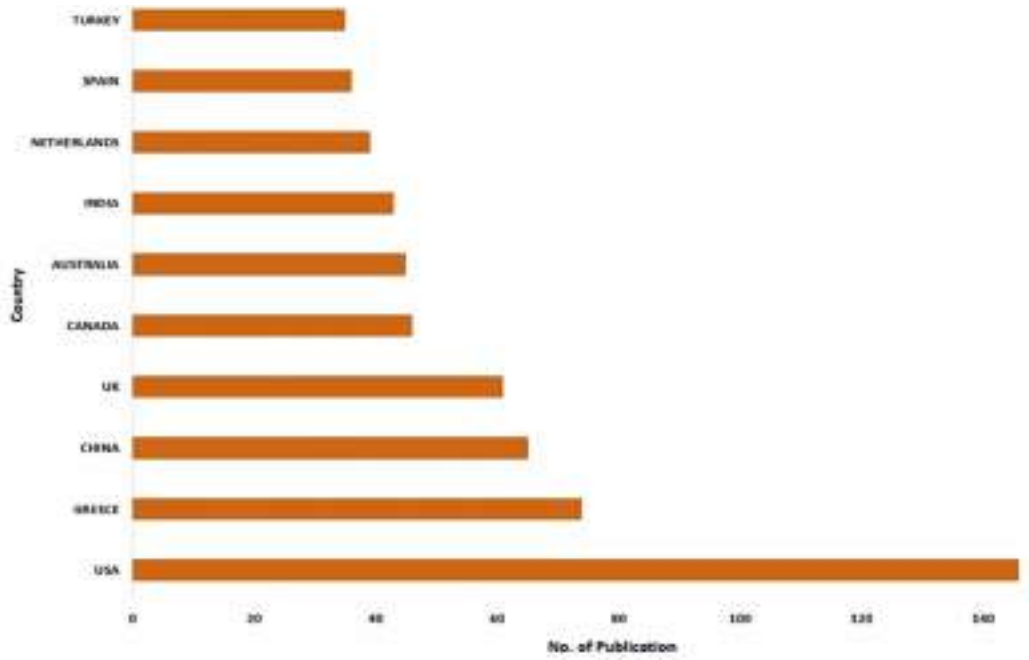


Figure 2. Top ten countries by scientific production in FCM-NRM research, 1995–2025

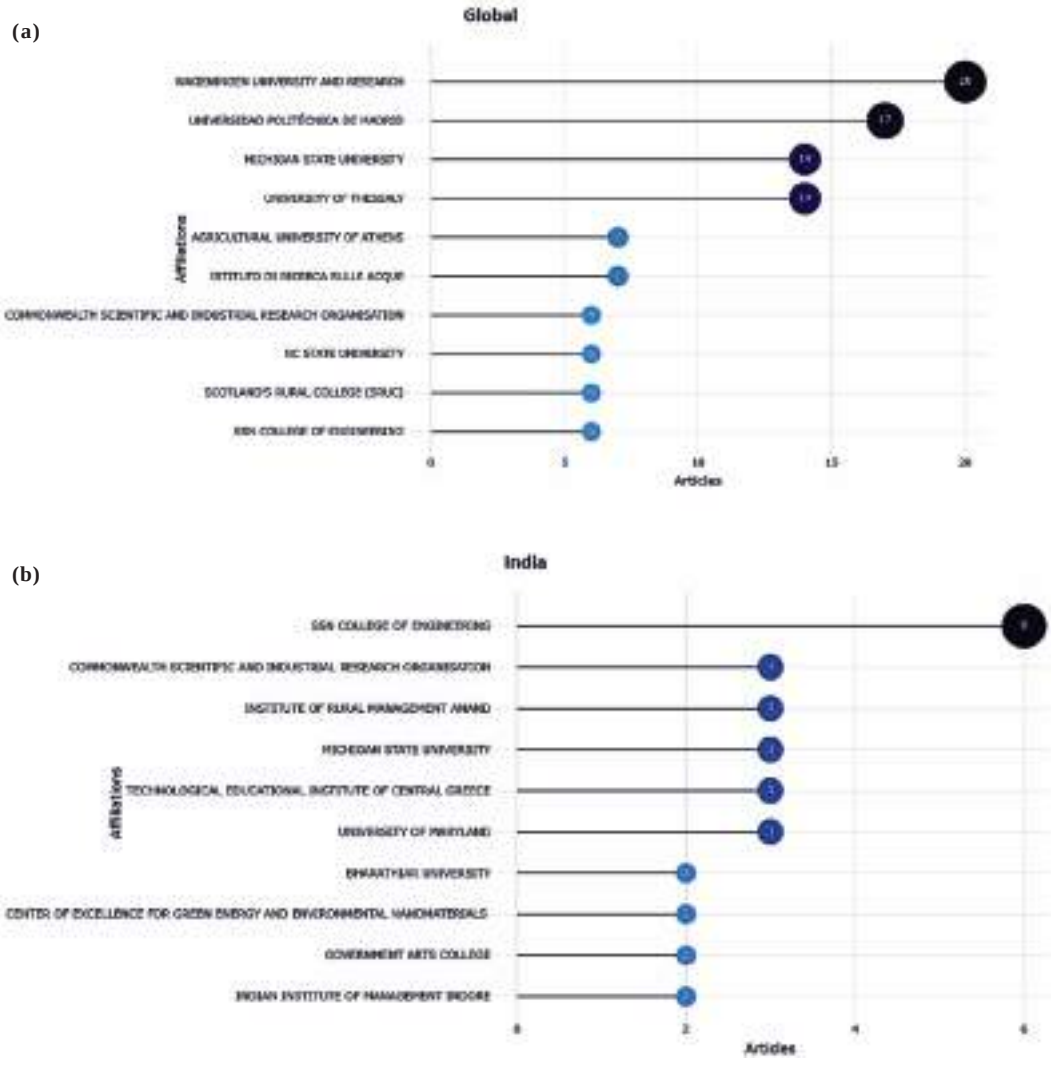


Figure 3. Top ten most productive institutions: (a) global and (b) India

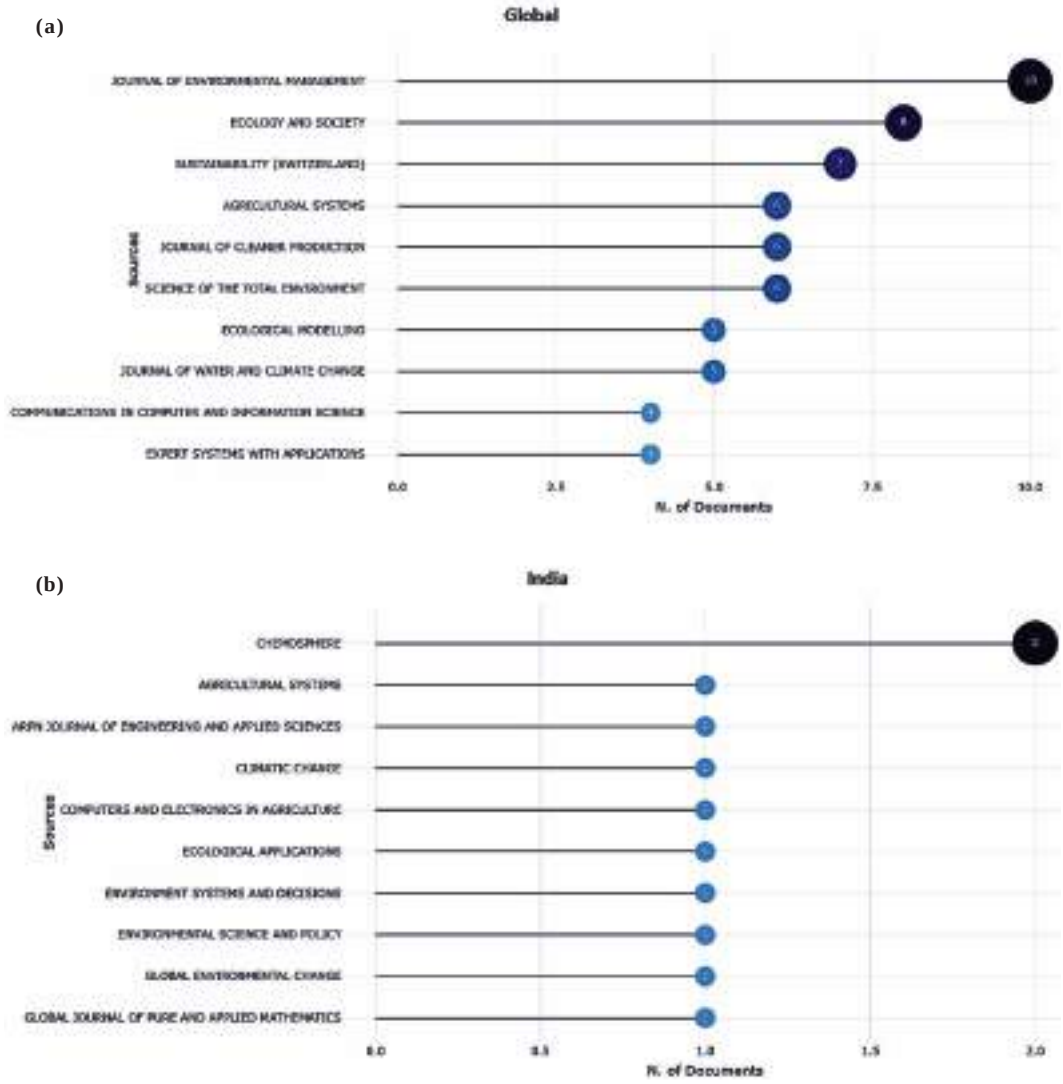


Figure 4. Top ten publishing sources by document count: (a) global and (b) India

Karavas (2015, *Energy Conversion and Management*) ranked first with 272 citations. Gray S.A. (2015, *Ecology and Society*) came second with 245, and Özesmi and Özesmi (2003, *Environmental Management*) third with 188 citations, suggesting longer term impacts and staying power of early participatory FCM work in environmental research (Figure 6).

In India, Singh (2021, *Journal of Cleaner Production*) drew the most citations at 109, followed by Gray (2018, *Ecological Applications*) at 101 (Figure 6). Goswami (2021, *Agricultural Systems*) ranked third with 66 citations marking a strong return for a study published just four years prior. The work examined FCM applications in Indian agricultural systems, and its citation record suggested that integrating stakeholder knowledge into farm-level NRM decisions struck a chord with researchers working on similar problems across South Asia.

Keyword analysis and conceptual structure: global and Indian perspectives

Indian keywords broadly mirrored global patterns but diverged in emphasis: human-centric terms such as “stakeholders” and “human” featured more prominently than in the global set, whereas the global corpus leaned more heavily on technical terms like “fuzzy rules” and “knowledge representation.” This divergence likely reflects India’s stronger orientation toward participatory field applications rather than algorithmic development. Terms such as “artificial intelligence” and “cognitive systems” also appeared in the Indian literature, indicating that researchers had begun connecting FCM with newer computational frameworks in applied NRM contexts (Figures 7a, 7b).

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The global Keyword Co-occurrence Network is larger and more complex (Figure 8a, 8b). Two dominant nodes, fuzzy cognitive mapping and fuzzy cognitive maps, form the network’s core. The red-orange cluster (2018–2020) includes participatory modelling, mental models, social-ecological systems, and natural resource management, showing recent emphasis on participatory and ecological applications. Older keywords (blue-purple, 2010–2012) include decision making and fuzzy sets, reflecting early

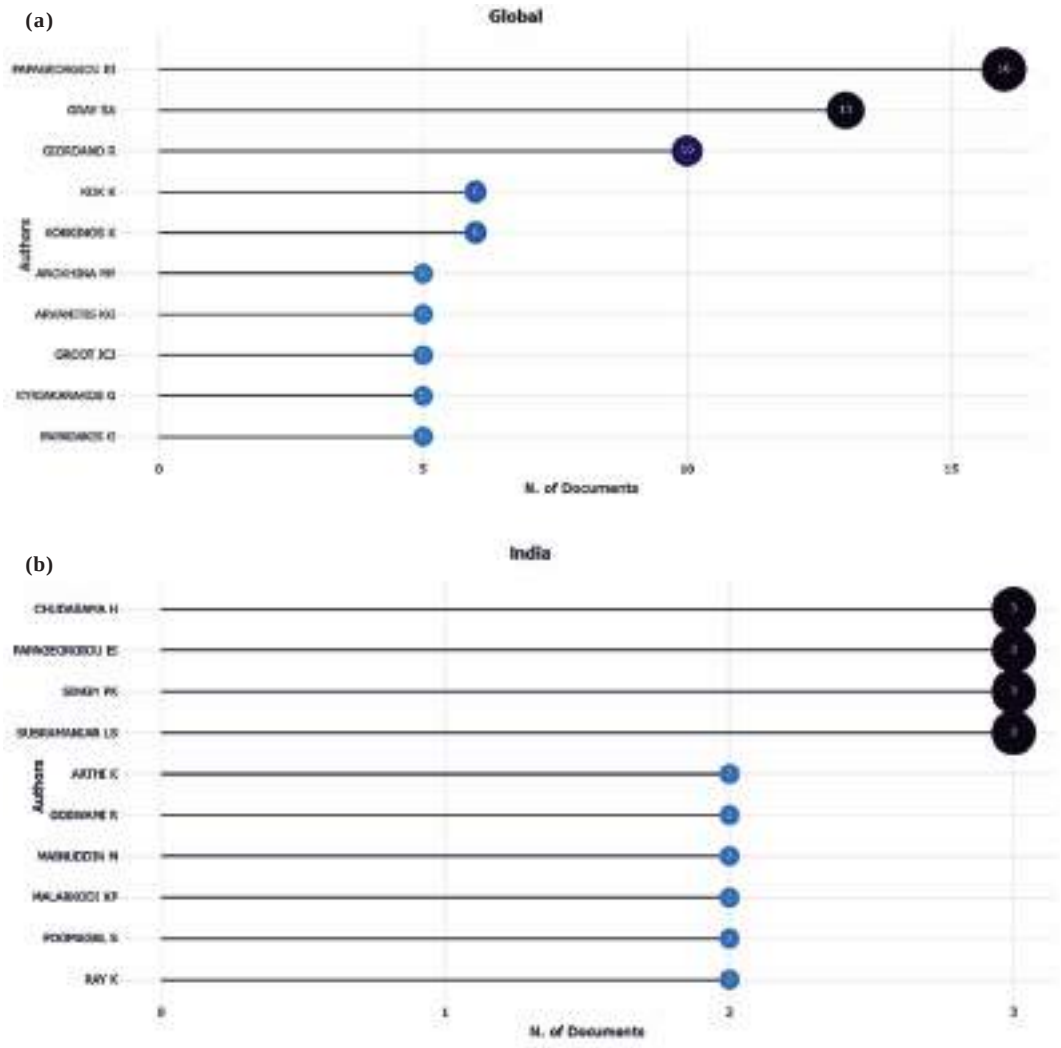


Figure 5. Most productive authors by publication count: (a) global and (b) India

methodological foundations. Stakeholders, sustainability, and agriculture serve as connecting themes across time periods. By contrast, the Indian co-occurrence network is smaller and more tightly focused. The red-orange cluster (2021–2022) centres on fuzzy cognitive maps, sustainability, stakeholders, water management, and environmental protection, reflecting India's recent policy-oriented turn. The blue-purple cluster (2018–2019) groups agriculture, fuzzy systems, fuzzy rules, and cognitive systems, representing the earlier technical phase. Fuzzy mathematics bridges both clusters, suggesting that quantitative formalisation remains a common methodological thread as the field shifts from algorithm-centric to application-centric research.

Thematic analysis of Indian studies

To complement the bibliometric findings, qualitative analysis of abstracts from India-based FCM studies directly addressing agriculture, NRM, and rural development yielded five thematic clusters (Table 2).

Human–environment conflict and ecological risk

Banerjee et al. (2025) applied FCM to model human–elephant conflict in a forested region, translating expert and community mental models into structured risk simulations. Alam et al. (2025) used FCM to examine the social-ecological risks of deep-sea mining. Both studies employed scenario comparison to reveal non-linear system dynamics that conventional linear assessments cannot capture, and recommended preventive and restorative management strategies over reactive responses.

Climate change adaptation and disaster resilience

Singh and Chudasama (2017) assessed community preparedness to cyclones in coastal Odisha; Singh and Chudasama (2020) examined climate adaptation pathways across arid and semi-arid Indian regions, while Panja et al. (2026) traced resilient pathways for climate-resilience agriculture in the coastal zones. Goswami et al. (2021) integrated FCM with qualitative research to explore resilience strategies for smallholder systems disrupted by COVID-19. Goswami et al. (2024) also examined resource recycling and land management for scaling zero-tillage potato cultivation in the coastal Sundarbans. Collectively, these studies demonstrated that climate adaptation was inherently multi-systemic; institutional factors like credit access, extension services, local governance were consistently identified as critical mediators between environmental shocks and household resilience.

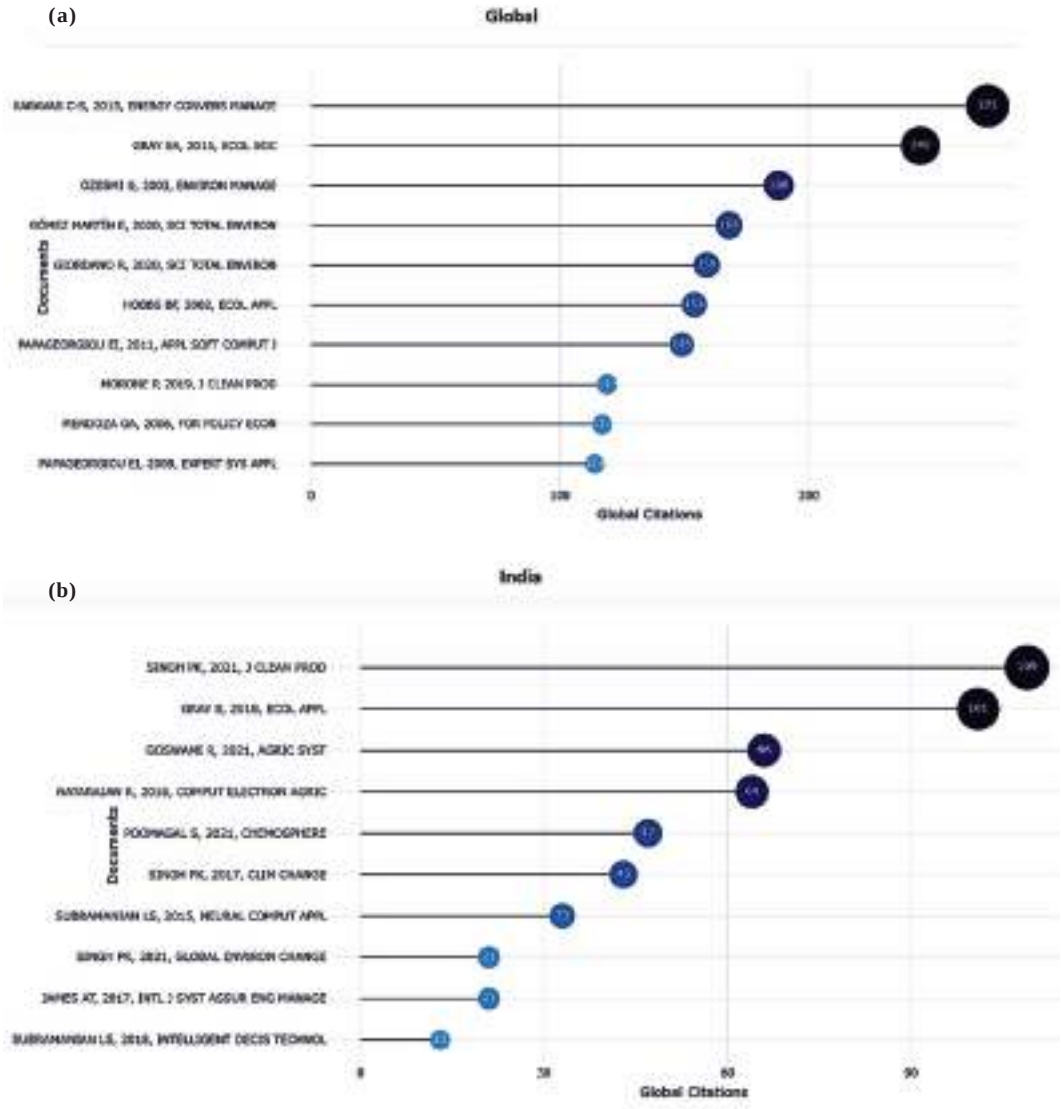


Figure 6. Most cited documents by total citation count: (a) global and (b) India

Table 2. Thematic summary of India-based FCM studies in NRM

Theme	Key studies	FCM application
Human–Environment Conflict & Conservation	Alam et al. (2025); Banerjee et al. (2025)	Stakeholder mental models; risk scenario simulation
Climate Change Adaptation & Disaster Resilience	Goswami et al. (2021, 2024); Singh & Chudasama (2017, 2020); Panja et al. (2026)	Pathway evaluation and resilient pathway identification; multi-stakeholder scenario planning
Sustainable Agriculture & Resource Management	Goswami et al. (2021, 2024); Haldar et al. (2026)	Resource recycling; land management; livelihood diversification and improvement
Precision Agriculture & Crop Yield Prediction	Anantharaj & Thangavelu (2015); Jayashree et al. (2015); Malarkodi & Arthi (2018); Natarajan et al. (2016)	Hybrid learning (FCM + ML); classification and yield prediction
Methodological Development	Jenitha (2017); Gray et al. (2017)	Participatory FCM frameworks; hybrid water demand prediction

Sustainable agriculture and resource management

Goswami et al. (2021, 2024) and Haldar et al. (2026) addressed resource recycling, land management and livelihood improvement as interdependent variables, with FCM providing the relational structure to model co-dependencies. Differentiated. These studies underscored that effective interventions must be differentiated by farm type, with particular attention to constraints specific to smallholders.

Precision agriculture and crop yield prediction

Jayashree et al. (2015), Anantharaj and Thangavelu (2015), Natarajan et al. (2016) and Malarkodi and Arthi (2018) applied



Figure 7. Most frequent author keywords in titles and abstracts: (a) global and (b) India

FCM, frequently hybridized with machine learning algorithms, to yield prediction for commercially significant Indian crops (coconut, sugarcane, groundnut, red chilli). These studies demonstrated that integrating expert domain knowledge with data-driven learning outperforms purely data-driven approaches in low-data, knowledge-rich agricultural settings. The focus on these crops reflects their strategic importance to India's agricultural policy.

Methodological development

Gray et al. (2017) advance the "Four Ps" framework i.e. Purpose, Processes, Partnerships, Products to address recurrent shortcomings in participatory FCM research, including issues of replicability, process transparency, and stakeholder engagement quality. Jenitha (2017) integrates FCM within a hybrid computational architecture for water demand prediction, demonstrating FCM's modularity within larger algorithmic systems.

Cross-cutting observations

Across all themes, Mental Modeler (https://www.mentalmodeler.com/) was frequently cited as the primary web platform for participatory FCM construction, while Python and MATLAB support data-driven implementations. Empirical studies span geographically diverse contexts like the Sundarbans delta, arid Rajasthan, the Malabar Coast, semi-urban Chennai, and cyclone-affected coastal Odisha, demonstrating FCM's applicability across varied socio-ecological settings. Scenario analysis, methodological triangulation (combining FCM with interview analysis, focus group discussions, and machine learning), and explicit policy orientation were hallmarks of the Indian FCM literature.

Taken together, Indian FCM research reveals a field that is small in volume but methodologically diverse and thematically aligned with pressing national priorities–climate adaptation, food security, and stakeholder-driven resource governance–positioning FCM as a versatile tool for evidence-based NRM decision-making in the Indian context.

DISCUSSION

This bibliometric analysis confirms that NRM-related research is a growing, globally distributed field with consistent citation impact and steady thematic evolution spanning three decades (1995 to 2025). The trajectory from technical modelling toward participatory planning, ecosystem services, and climate-oriented sustainability applications is consistent with broader shifts observed across environmental and sustainability science (Ellili, 2024). By utilizing a Scopus-based bibliographic dataset, this study conducts an inclusive and structured analysis of the field, with the overarching aim of advancing scholarly knowledge and providing evidence-based insights into current research trends and emerging future directions.

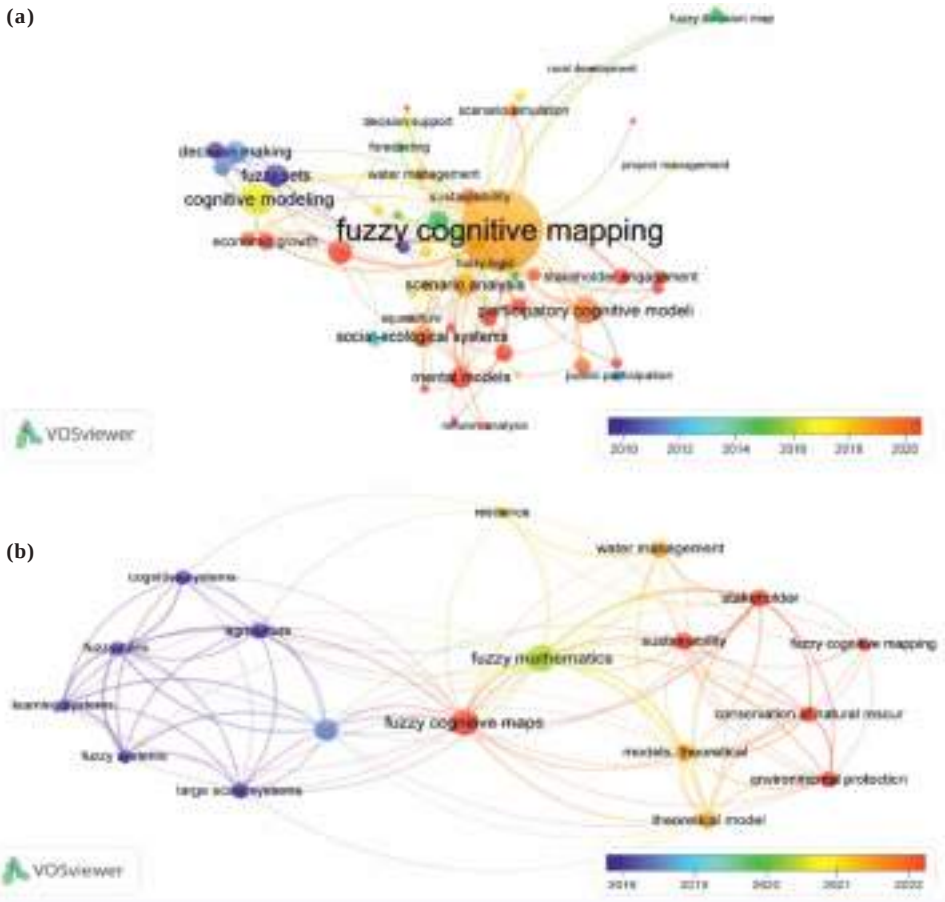


Figure 8. Keyword co-occurrence network and thematic temporal evolution in FCM-NRM literature: (a) global network and (b) India network

The United States leads in overall research output, reflecting sustained federal and institutional investment in environmental and agricultural research through agencies such as USDA and NSF. Greece's disproportionately high output can be attributed to concentrated research groups in computational intelligence, particularly around scholars like E.I. Papageorgiou, who have advanced FCM methodology and its environmental applications. Wageningen University and Research (Netherlands), with its longstanding strengths in agro-ecological and natural resource systems, leads institutional output globally. The *Journal of Environmental Management* and *Ecology and Society* serve as primary publishing venues within the field, signalling meaningful integration across both applied management communities and ecological theory scholarship. At the author level, Karavas et al. commands the leading position in the global citation landscape with 272 citations, reflecting significant scholarly influence in shaping the field's intellectual direction. The field further demonstrates strong collaborative dynamics, with cross-institutional and cross-national partnerships increasingly characterizing its output over the observed timespan.

India's NRM literature exhibits comparable citation impact and a distinctive thematic profile. The prominence of SSN College of Engineering (Tamil Nadu) as the leading institutional contributor reflects growing and concentrated domestic investment in NRM-related research. At the author level, P.K. Singh leads the Indian citation landscape with 109 citations, underscoring meaningful scholarly influence within the national context. Journals such as Chemosphere, Agricultural Systems, and Climatic Change serve as primary publishing outlets for India-based research, indicating interdisciplinary engagement across environmental, agricultural, and climate domains. Indian studies increasingly emphasize stakeholder engagement, human perceptions, agriculture and decision-support systems, where thematic priorities align closely with global research trajectories while simultaneously addressing India's heterogeneous agro-ecological contexts and community-specific NRM challenges. From a policy standpoint, these findings suggest that FCM can serve as a practical tool for participatory policy design, enabling policymakers to incorporate diverse stakeholder mental models into scenario planning for climate adaptation, resource allocation, and disaster preparedness.

Several limitations warrant acknowledgement and require consideration when interpreting the findings of this study. First, the exclusive reliance on Scopus as the sole bibliographic database restricts the comprehensiveness of the analysis, potentially excluding relevant literature indexed elsewhere. Future studies incorporating Web of Science, Google Scholar, or other complementary databases would substantially broaden coverage and enhance the representativeness of findings. Second, the India-specific thematic analysis is conducted manually using MS Word, without the assistance of dedicated qualitative research software. Software-assisted analytical approaches such as NVivo, ATLAS.ti, or comparable platforms have the potential to considerably improve both the methodological rigour and the reproducibility of thematic outcomes in future investigations. Third, network-based analytical methods

including co-authorship analysis, co-citation analysis, bibliographic coupling, and related structural approaches remain beyond the scope of the present study owing to time constraints. Future research incorporating these methods would provide a richer and more architecturally nuanced understanding of the field's intellectual structure and collaborative networks. Finally, existing studies tend to concentrate on a single domain of natural resources, with limited cross-domain integration within any unified research framework. Future investigations that deliberately incorporate multiple domains spanning agriculture and allied sectors, forestry, water resources, and beyond have the potential to offer a substantially more holistic understanding of the broader NRM landscape.

CONCLUSION

FCM-based research in NRM demonstrates robust global growth, high citation impact, and expanding international collaboration, led by the United States and Greece with the field maturing from technical modelling foundations toward applied, participatory, and sustainability-oriented inquiry India's FCM literature, though smaller in volume, is dynamic and growing. Institutions including IIT Delhi, IRMA, and RKMVERI contributing to a distinctive research agenda spanning precision agriculture, climate adaptation, conservation conflict and disaster resilience. Indian FCM research serves three interrelated functions,– capturing stakeholder mental models, analysing system complexity and supporting scenario-based policy decisions. As artificial intelligence and digital platforms become more deeply integrated with FCM methodologies, the field is well-positioned to contribute to global sustainability, equity, and resilience agendas, particularly in the data-scarce, knowledge-rich settings that define much of rural India. Future research should explore the integration of artificial intelligence techniques, such as deep learning for automated weight calibration and large language models for participatory elicitation, with FCM methodologies to enhance scalability and predictive accuracy.

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Research Article

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Occupational Determinants of Migration Behaviour among Lanjia Saora Tribal Youth in Odisha, India

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HIGHLIGHTS

- Financial support for family was the most significant factor affecting migration. Occupational factors are more critical determinants of migration behaviour than socio-economic factors, and a lack of year-round employment is a major push factor for migration.
- A significant proportion of respondents have a high migration intensity, suggesting that migration is a livelihood strategy.
- Positive values of languages known and working experience increased migration behaviour, suggesting the role of skills, experience and adaptability in driving migration.

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ABSTRACT

Migration has emerged as a major livelihood strategy among tribal communities due to limited local opportunities. In the current study, conducted during 2025-26, a Migration Behaviour Index (MBI) was used to examine the migration behaviour of Lanjia Saora tribal respondents residing in Gajapati and Rayagada districts of Odisha. A multistage sampling and ex post facto research design were used to select 180 sample tribal youth. The analysis of migration was limited to migrant respondents, while the Correlation and Random Forest analyses were performed on the whole sample. Findings indicated that 64.70 per cent of the respondents were involved in temporary rural-urban migration, mainly due to financial needs and unavailability of local opportunities. Occupational variables were more strongly associated with MBI than demographic variables, while employment during the closed season emerged as a major determinant. The Random Forest model performed well in prediction (Test $R^2 = 0.766$). The study indicates that migration is a distress driven livelihood strategy and there is a need to boost rural skills and entrepreneurship development interventions.

INTRODUCTION

One of the Particularly Vulnerable Tribal Groups (PVTGs) is the Lanjia Saora tribe, which is mainly found in the Gajapati and Rayagada districts of Odisha. The tribe has endured livelihood challenges, including subsistence farming, limited access to resources, and socio-economic marginalisation (Nallala et al., 2023). Traditional occupations and low agricultural productivity do not generate sufficient income to support their livelihoods, leaving their livelihoods very vulnerable and unpredictable. The socio-economic activities of the Lanjia Saora people are gradually changing, particularly in the younger generation (Ghosal et al., 2024). As a dynamic and aspirational group, youth are vital to the future of tribal communities. Youth aspirations Refer to expectations, goals,

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and ambitions of youths regarding their livelihoods, education, and general living standards (Sai et al., 2024). These ambitions among tribal youth are increasingly shaped by exposure to external environments, education, and changing socio-economic conditions. Nevertheless, the distance between ambitions and locally accessible opportunities can be challenging, compelling young people to seek alternative ways of living (Pandey et al., 2019; Ghosh et al., 2025b).

Migration has become a major livelihood phenomenon in villages, especially among tribal societies, which have low employment rates and high economic insecurity. In this case, people migrate to find more suitable income, better working conditions and living standards. Migration is therefore a way to diversify livelihoods, manage risk, and respond to economic distress (Pal et al., 217; Koirala & Bashyal, 2025). In recent years, rural-to-urban and seasonal migration has increased significantly, especially among marginalised groups such as tribal populations. The Lanjia Saora tribe, residing predominantly in the districts of Gajapati and Rayagada in Odisha, is one such vulnerable group in which migration plays a crucial role in sustaining livelihoods (Sabar, 2020). Factors such as lack of local employment, low agricultural productivity, and limited access to resources often act as push factors, while better job opportunities and higher wages act as pull factors.

While a number of studies have examined migration from an economic perspective, migration behaviour is a complex phenomenon and is influenced by demographic, occupational, and social characteristics (Kuzur & Minz, 2021). Hence, it is necessary to analyse migration behaviour using an index to reflect its multidimensional nature. In this regard, the current study attempts to understand the migration behaviour of the Lanjia Saora tribal respondents using a Migration Behaviour Index (MBI) and to identify the major socio-economic determinants of migration behaviour.

METHODOLOGY

The study examined the migration patterns of the Lanjia Saora tribal respondents in Odisha in 2025-2026 and adopted the *ex-post-facto* design and a multistage sampling technique. The Gajapati and Rayagada districts were chosen as they have large Lanjia Saora populations. A block was selected in each district, Gumma (Gajapati) and Gunupur (Rayagada), and three villages were selected in each block, making a total of six villages. From each village, 30 respondents were randomly selected. The structured interview schedule was pre-tested and used to collect primary data, including demographic features, household factors, occupational features, and migration variables (Bhattamishra, 2020).

Migration behaviour (MBI) was considered the dependent variable, whereas age, marital status, languages known, occupational engagement, working days per month, employment during the closed season, sanitation facility, fuel used for cooking, nature of employment, and work experience were considered independent variables. To ensure occupational homogeneity, the 27 students were excluded from the migration indicators. Mean score rankings of migration reasons were analysed only for respondents with migration experience, as non-migrants lacked appropriate data. The migration behaviour was measured using a composite Migration Behaviour Index (MBI), derived by summing variables including migration status, nature and reasons of migration, decision-making processes, migration networks, remittance behaviour, and visit frequency. Employment during closed season, operationally defined as engagement in any income-generating activity during the lean agricultural season, typically May–June and November–December in southern Odisha. The reliability of the Migration Behaviour Index (MBI) was assessed using Cronbach's Alpha ($\alpha = 0.938$), indicating good internal consistency among the indicators. The index was calculated as the average of all selected variables **(**Gaikwad et al., 2020).

$$MBI = \frac{\sum_{i=1}^{n} X_i}{n}$$

where, X_i denoted the score of the ith migration-related variable and *n* represented the total number of variables included in the index (Borozan et al., 2024).

Pearson's correlation analysis was conducted, and the correlation matrix was created in RStudio. The MBI was predicted using a Random Forest regression model in Python. The 'Random' in Random Forest arises from two sources: (1) bootstrap aggregation (bagging), wherein each tree is trained on a random sample with replacement of the training data; and (2) feature randomisation, wherein a random subset of predictor variables is evaluated at each node split, reducing variance and improving generalisation, the full sample of 180 respondents was used to ensure robustness and generalizability.

RESULTS

Migration emerged as a major livelihood strategy among the respondents, with nearly two-thirds (64.70%) engaged in migration, indicating limited local employment opportunities. The migration pattern is entirely temporary and rural-to-urban, which suggests that people are not leaving their villages permanently but are moving temporarily in search of work. Most migrants (88.88%) travel alone rather than with their families. At the same time, migration decisions are largely influenced by family discussions (87.80%). Social connections play an important role in facilitating migration, with friends being the most common support network at 38 per cent, followed by Neighbours at 6.50 per cent, Relations and Agencies at 6 per cent, and 4.30 per cent. A large proportion of migrants (85.80%) are engaged in non-agricultural work in their migrated area, and the other (14.14%) are engaged in agriculture-related work. Additionally, migration contributes significantly to household income, as most migrants likely (62.20%) send money back home regularly. The majority of about (66.12%) remit between Rs. 6000–10000 per month, typically on a monthly basis, highlighting the importance of migration as a financial support system for their families.

Reasons for migration among respondents

The comparison of migration reasons by frequency distribution and mean score ranking showed that financial support for family was the most significant factor affecting migration, with the highest mean score (4.83) and a significant percentage of respondents strongly agreeing. The second factor that made the greatest contribution to migration was perceived career development

suitability in the native area (Mean = 4.65), where respondents faced structural and developmental constraints in their place of origin. Parental pressure was the third most common (Mean = 4.04), indicating moderate social pressure on migration decisions. The availability of better jobs, on the other hand, had the lowest mean rating (3.72), with a high percentage of respondents rating it neutral, indicating uncertainty about its importance as a major motivating factor for migration (Table 1).

Table 1. Distribution of Respondents Based on Migration Indicators

Variable	Category	Percentage
Migration Status (n=153)	Yes	64.70
	No	35.29
Migration Participation (n=99)	With Family	11.11
	Alone	88.88
Decision Making (n=99)	Consulting with Family	87.80
	By Own Self	12.12
Migration Network (n=99)	Friends	38.00
	Neighbours	6.50
	Relations	6.00
	Agents/Agency	4.30
Nature of Work in the Migrated Area (n=99)	Non-agriculture	85.80
	Agriculture	14.14
Sending Money Home (n=99)	Yes	62.20
	No	37.37
Amount Sent per Month in Rs. (n=62)	Rs. 6000–10000	66.12
	Rs. 1000–5000	33.87

A total of 180 respondents were involved in the study: 99 (64.70%) migrants, 54 (35.29%) non-migrants, and 27 Student respondents. Among migrant respondents, 62 (62.6%) reported sending money to their families, while the remaining 37 (37.4%) did not practice money sending. It was also found that all migrant respondents were temporary migrants, having migrated from rural to urban areas. Among respondents who send remittances (n = 62), all (100%) reported sending money once a month, suggesting that migrant households remit monthly (Table 1).

All 180 respondents (including 27 students) were included in the MBI computation as the index reflects the overall migration context. Students were excluded only from migration-indicator analyses (Table 1) and mean score rankings.

MBI (Migration Behaviour Index)

The Migration Behaviour Index (MBI) distribution of respondents showed that the largest proportion (45%) is in the Low migration category, with 33.8% in the High migration and 21.1% in the Moderate migration categories (Table 2). The mean score of the MBI (2.46) suggests that the respondents have a moderate level of migration behaviour. However, the number of respondents in the Low category is high, suggesting that migration is a common livelihood strategy in the study region. The variation in MBI scores (1.43-3.68) and the standard deviation (0.88) suggest that there is a considerable difference in migration behaviour. This variation in behaviour suggests that some respondents may be only slightly involved in the migration process, while a large percentage are actively engaged in migration activities. Within the study area, migration behaviour is not uniform; a significant proportion of respondents have a high migration intensity, suggesting that migration is a livelihood strategy.

Table 2. Distribution of respondents based on Migration Behaviour Index

Category	Percentage
Low	45.00
Moderate	21.11
High	33.88
Total	100.00

A correlation analysis was conducted to understand the association between a set of socio-economic and occupational variables (independent variables) with the Migration Behaviour Index (MBI) (dependent variable). The results showed that occupational factors such as involvement in occupation (r = 0.54), work experience (r = 0.54), type of work (r = 0.43) and days worked per month (r = 0.45) have moderate positive correlations with MBI, suggesting that those who are more involved in their work and have more work experience have higher levels of migration behaviour. Socio-economic variables such as languages known (r = 0.45) and sanitation facilities (r = 0.39) also displayed moderate positive correlations with MBI, while age (r = 0.27) and fuel used for cooking (r = 0.29) had weaker positive correlations. On the other hand, working in the closed season displayed a moderate negative association with the MBI (r = -0.37), highlighting that working in the closed season is likely to reduce migration. In all, the findings suggest that occupational factors are more critical determinants of migration behaviour than socio-economic factors, and a lack of year-round employment is a major push factor for migration.

Random forest analysis

The data were split into training (80%) and testing (20%) sets using a fixed random state. The Random Forest model used 100 decision trees (n_estimators = 100), with no maximum depth restriction, minimum samples per leaf = 1, and maximum features = “sqrt” at each split.

Table 3. Model Performance Metrics for Training and Testing Data

Dataset	R^2	MAE	MSE	RMSE
Training	0.9442	0.1319	0.0431	0.2077
Testing	0.766	0.2193	0.1657	0.4071

To determine the model’s accuracy and generalisation capability, it was evaluated on both the training and test data. On the training dataset, the model showed a good fit (R^2 = 0.9442), and low error values (MAE = 0.1319, MSE = 0.0431, RMSE = 0.2077), suggesting good predictive power. The testing results show a high level of model fit (R^2 = 0.766), indicating good model fit, though slightly worse than on the training data. The larger error values (MAE = 0.2193, MSE = 0.1657, RMSE = 0.4071) suggest a slight loss in accuracy. This difference between training and test results indicates some overfitting; nevertheless, the model shows reasonable generalisation and is well-suited for predicting migration.

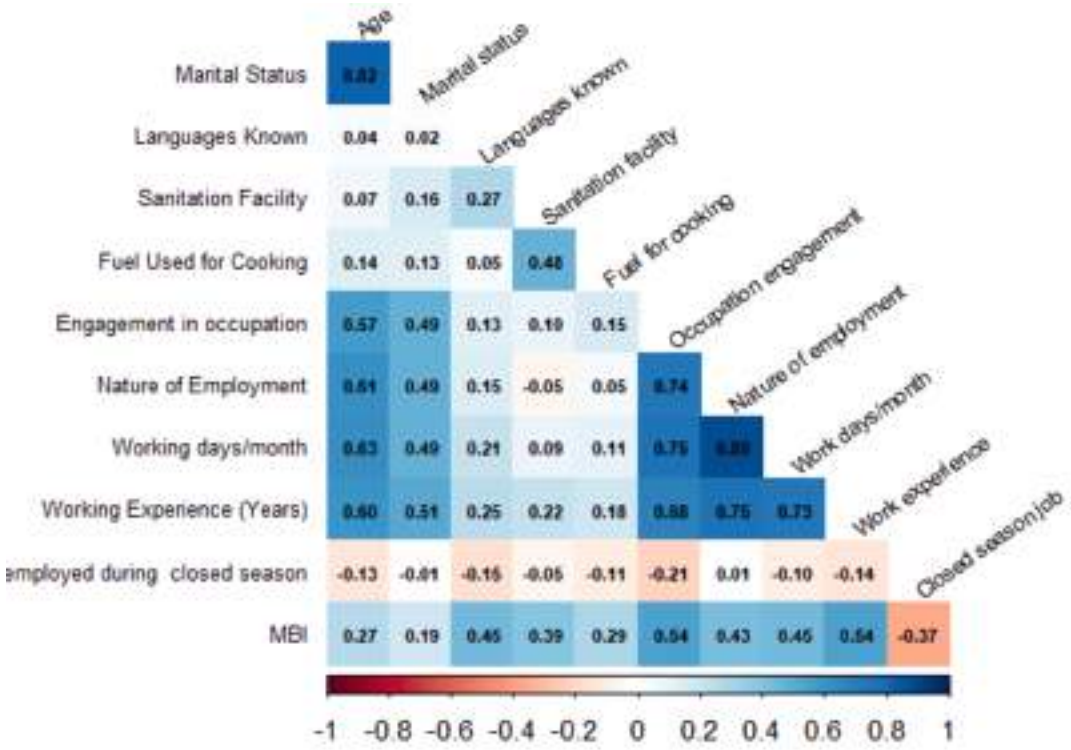


Figure 1. Correlation between MBI and selected variables

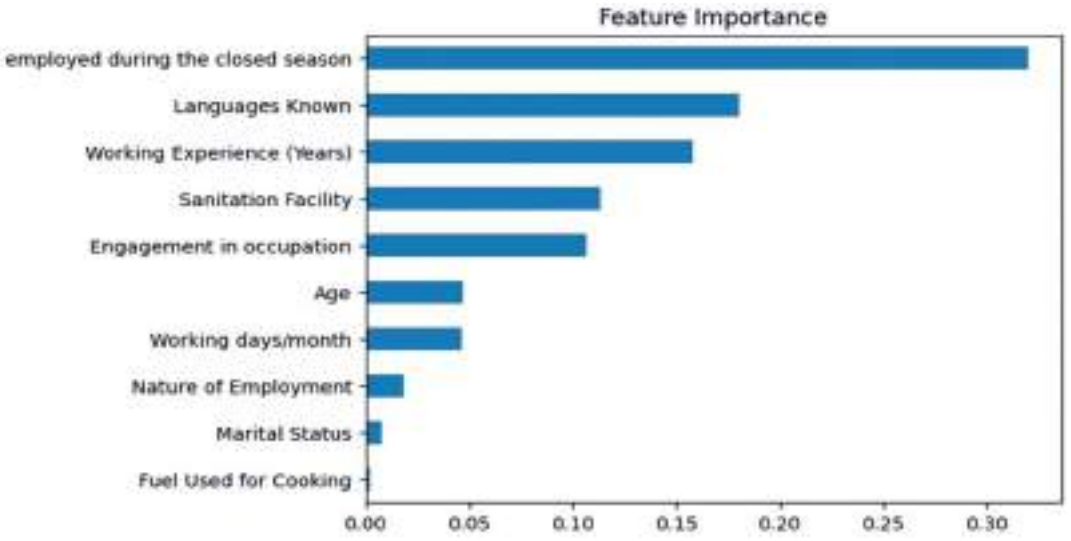


Figure 2. Feature Importance of Predictor Variables Influencing Migration Behaviour Index (MBI)

The feature importance analysis revealed employment during the closed season as the top predictor for MBI, followed by languages known and years of employment. This finding highlights the significance of stable employment and individual capacity in influencing migration. Furthermore, sanitation, participation in occupation, and toilet facilities were found to have a mid-level influence, while the fuel used for cooking, marital status, and type of employment have a low impact on the model's results.

Additional insights from the SHAP (SHapley Additive exPlanations) analysis showed which variables positively or negatively influence migration behaviour. It was found that being unemployed in the closed season has a significant positive impact on MBI, supporting its status as a push factor for migration. Also, positive values of languages known and working experience increased migration behaviour, suggesting the role of skills, experience and adaptability in driving migration. Conversely, variables with lower SHAP values had little influence on the model. Overall, the results highlight that the lack of seasonal employment, and human capital characteristics, are critical factors driving migration behaviour among respondents.

DISCUSSION

The study confirms that migration is the most common livelihood strategy among the Lanjia Saora tribal respondents, with 64.70 per cent involved in it. This reflects structural factors, including the lack of local jobs, low agricultural productivity, and

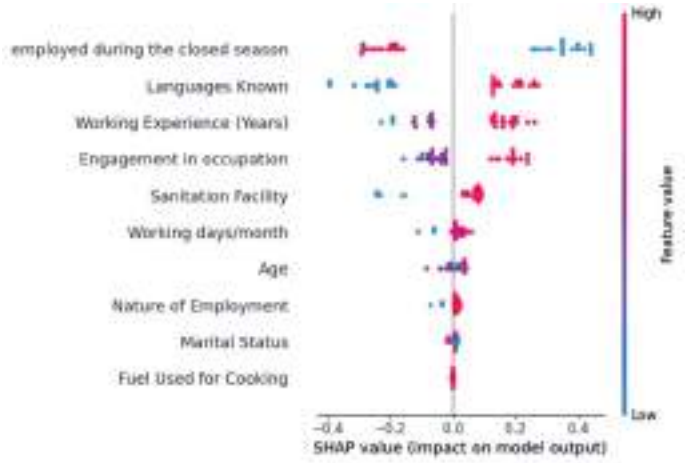


Figure 3. SHAP Summary Plot Showing the Contribution of Predictor Variables to Migration Behaviour Index (MBI)

socio-economic marginalisation, which are widespread in the tribal areas of Odisha and central India (Mohanty, 2024). In recent decades (25 years), rural-urban migration has accelerated due to industrialisation and service-sector growth, and the declining profitability of farming. Consequently, Tribal youth are abandoning traditional livelihoods in favour of other opportunities (Ngadi et al., 2023). Push and pull factors play an important role in migration, with employment-related factors being significant (Roy et al., 2022). The prevalence of temporary rural-urban migration indicates it is primarily seasonal, temporary and motivated by a lack of employment security.

The research also suggests migration is more compelled rather than voluntary economic activity. Economic responsibilities to family and a lack of employment opportunities in the rural region are prominent factors (Haq et al., 2025). Unsteady income, lack of employment, and frequent crop failures are major push factors, while better economic opportunities, higher wages and better living conditions are pull factors (Maurya et al., 2022). Factors such as occupation, work experience, and economic incentives positively affect migration, suggesting that migration is more likely when farmers are more adaptable (Sai et al., 2024). The high participation in non-farm sectors indicates a transition, as tribal labour enters urban informal sectors. The prevalence of individual migration suggests labour market conditions favour flexible forms of work (Kujur & Minz, 2021).

Migration also functions as an important source of household income, with regular remittances supporting rural livelihoods despite modest earnings. Variability in the Migration Behaviour Index (MBI) suggests heterogeneity in migration patterns, driven by differences in access to resources, opportunities, and social networks. Socio-economic and psychological factors such as age, education, non-farm skills, income expectations, risk orientation, self-reliance, and self-confidence are positively associated with migration behaviour (Anamica & Sujeetha, 2017; Mourya et al., 2022). These findings reinforce the role of declining agricultural profitability and limited rural employment in driving migration (Gaikwad et al., 2020).

Occupational factors exert a stronger influence on migration behaviour than demographic characteristics. Extent of occupational engagement, work experience, and working days per month show positive relationships with migration (Bernzen et al., 2019), whereas the availability of off-season employment shows a negative relationship, suggesting seasonal unemployment as a key push factor (Selod & Shilpi, 2021). The Random Forest and SHAP analyses further confirm that employment insecurity is the most influential predictor, along with human capital attributes such as language proficiency and work experience (Ghosh et al., 2025a). Structural and human capital factors play complex roles in driving migration within the Lanjia Saora tribal community (Sandesh et al., 2020). Government strategies should prioritise improving rural livelihoods through skill training, agricultural productivity and extension. Youth participation in agriculture through enterprise development has successfully enhanced livelihoods, social inclusion, and access to information (Mohanty et al., 2025).

CONCLUSION

The study identified migration as the primary livelihood strategy among Lanjia Saora tribal respondents in southern Odisha, driven by limited local job opportunities, poor agricultural output and seasonal livelihood insecurity. Migration is temporary, urban-oriented and compulsory rather than voluntary. Occupational factors, such as work engagement, experience and employment availability, influence migration behaviour more than demographic factors. Migration promotes household income through frequent but unstable remittances. The findings highlight the need to enhance rural employment, skill development and agricultural productivity, as well as to diversify livelihoods. Addressing seasonal unemployment and underdeveloped human capital can reduce distress-motivated migration and stabilise livelihoods in tribal areas. The results suggest scaling up MGNREGA employment during lean agricultural periods; improving skill training under DDU-GKY and PM Kaushal Vikas Yojana for tribal youth; enhancing farm-based entrepreneurship through schemes like ARYA; and strengthening agricultural extension services to boost income and productivity.

DECLARATIONS

Ethics approval and informed consent: Throughout the study, the respondents were asked for their informed consent.

Conflict of interest: The research was carried out without any financial or commercial ties that might be seen as a potential conflict of interest, according to the authors. The authors affirm that they carefully examined, amended and edited the content as necessary when preparing this work. The final content of this publication is entirely the authors' responsibility.

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Research Article

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Agricultural Information Transfer among Tribal Farmers of Malkangiri Using Machine Learning

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HIGHLIGHT

- Personal localite contacts emerged as the most effective channel with the lowest information transfer gap of 34.61 per cent.
- Farming experience was the strongest predictor, contributing 36.80 per cent to model predictive power among tribal farmers.
- Ridge regression (CV $R^2 = 0.503$) outperformed random forest in generalisation, making it optimal for tribal extension programme design.

ARTICLE INFO

Keywords: Agricultural information transfer, Machine learning, Random forest, SHAP values, Tribal farmers.

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ABSTRACT

The study was carried out in 2026 to examine the extent of agricultural information transfer and the determinants of agricultural information transfer among tribal farmers of Malkangiri district of Odisha. Four blocks were selected purposively, and 30 farmers were randomly selected from each block through a multistage random sampling technique, constituting a total sample of 120 respondents. Primary data were collected using a pre-tested and structured interview schedule. Data were analysed using descriptive statistics random forest regression algorithm in Google Colaboratory, with SHapley Additive explanations values computed for explainable feature-level attribution. The agricultural information transfer was low to moderate across all five channels, ranging from the highest mean score for personal locality contact (1.96) to the lowest for private sector engagement (1.18; gap = 60.76%). Experience on farms and age were the most significant predictors, together explaining 66.77 per cent of the model's feature importance, with education having little influence. The training performance of the random forest model was good ($R^2 = 0.9159$), while it acknowledges the 0.4877 gap and attributes it to sample size and RF's sensitivity.

INTRODUCTION

Agricultural information is the lifeblood of rural transformation, as it helps farming communities access better technologies, improve the productivity of their operations, and maintain their livelihoods (Bhagat et al., 2004; Nain et al., 2015; Sandeep et al., 2022; Sanju et al., 2025). Even with significant investment in public extension systems, the lack of information continues to marginalise tribal communities in geographically isolated areas of India (Bora & Mahanta, 2022). This is more pronounced in the scheduled tribal belts of South Odisha, where physical isolation, linguistic diversity, and lack of extension staff with required training make the job difficult. The southernmost district of Odisha, namely, Malkangiri, is a typical example of the condition and has 58 per cent tribal population, with 52.24 per cent literacy rate (Panigrahi, 2019; Tripathy & Ranjitha, 2022).

For instance, Malkangiri's tribal farming communities, primarily Koya, Bonda, and Kondh communities, do not rely on formal extension services to provide agricultural guidance and information; instead, they use informal peer networks and

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traditional knowledge, as demonstrated by Ghosh et al. (2025). Although a number of government schemes, such as the Special Programme for Promotion of Integrated Farming and the Odisha Millet Mission, have enhanced crop diversification in some blocks, the transfer of technologies varies across the region (Odisha Department of Agriculture, 2022). Distress migration, limited access to extension workers, a lack of communication tools in tribal languages, and weak market linkage continue to hinder the smooth dissemination of agricultural information to communities (Panda et al., 2019; Jat et al., 2021; Niranjan et al., 2023; Saha et al., 2024).

Machine learning methods offer substantial promise for advancing the evidence base on agricultural information transfer. Conventional regression approaches, while widely employed in extension research, are limited in their capacity to model the complex, non-linear interactions among socioeconomic, psychological, and contextual variables that jointly determine a tribal farmer's information-seeking behaviour (Shukla et al., 2024). ML algorithms-including random forest, gradient boosting, and regularised regression-can simultaneously handle high-dimensional predictor spaces, rank feature contributions through SHAP values, and yield cross-validated performance estimates that reliably generalise to new populations (Khatri et al., 2024; High et al., 2025). These capabilities are particularly valuable for designing targeted, resource-efficient extension strategies in data-scarce tribal districts.

Although growing literature documents information-seeking behaviour among tribal farmers in North-East India (Syiem & Raj, 2015) and central India (Jat et al., 2021), empirical research applying ML-based modelling to agricultural information transfer in the tribal districts of southern Odisha remains conspicuously absent. The present study was therefore undertaken to assess the level of agricultural information transfer among tribal farmers in Malkangiri district.

METHODOLOGY

The study was conducted in the Malkangiri district of Odisha in 2026. Malkangiri district, situated in the southern part of Odisha, is home to a predominantly tribal population engaged in subsistence agriculture, making it contextually appropriate locale for examining agricultural information transfer. The district comprises 7 blocks, of which four blocks, namely Khairaput, Korukonda, Malkangiri and Mathili, were purposively selected on account of their significantly higher concentration of tribal farming households. Random sampling was used to select respondents in two stages. For the first stage, two villages were randomly selected from each selected blocks, resulting in eight study villages. In second stage, a complete enumeration of tribal farm households in each village was carried out to prepare the sampling frame. Subsequently, using random sampling, 15 farmers were selected from each village, yielding a final sample of 120 tribal farmers. Primary data were collected through personal interviews using a pre-tested, structured interview schedule. The interview schedule comprised items pertaining to 14 independent variables: age, education, occupation, livestock ownership, annual income, family size, family type, type of house, size of land holding, type of land holding, farming experience, social participation, innovativeness, and risk orientation. The dependent variable was the level of agricultural information transfer. Based on the frequency of access to and use of different sources of information, the information dissemination was measured using a three-point rating scale with response options of "Regular", "Occasionally" and "Never" (Shivamogga & Pujar, 2018). Accordingly, weighted mean scores were calculated for each information transfer dimension to facilitate comparison of their relative effectiveness. To quantify the extent of deficiency in information dissemination, the Information Transfer Gap (ITG) was computed using the following formula, ITG (%) = [(3 – Mean Score)/3] × 100, where 3 represents the maximum obtainable score on the scale. Additionally, a random forest regression algorithm was applied to model non-linear interactions among the 14 predictor variables and to generate SHAP (SHapley Additive exPlanations) values for explainable, feature-level attribution of model output. The RF model comprised 200 decision trees with a maximum depth of 10 and was implemented using Google Collaboratory (Google Colab), a cloud-based Python programming environment, through the scikit-learn library (Pedregosa et al., 2011). Model performance was evaluated using coefficient of determination (R^2), mean absolute error, root mean square error, and five-fold cross-validation R^2 to guard against overfitting. Statistical significance was set at the 5 per cent probability level throughout the analysis.

RESULTS

Table 1 presents the statement-wise mean scores and information transfer gap (ITG) percentages for the five identified channels of agricultural information transfer among tribal farmers of Malkangiri. Overall, the mean scores (ranging from 1.18 to 1.96 across the five statements) on a three-point scale. Transfer through personal localite was found to be the best channel, with a mean score of 1.96 and a corresponding information transfer gap of 34.61 per cent, indicating that personal localite or informal face-to-face interaction within the community remains the most predominant channel of agricultural information flow among tribal farmers. Extension participation (mean = 1.91; gap = 36.48%) and extension contact (mean = 1.85; gap = 38.38%) were in the substantial range, while very little information transfer occurred through mass media (mean = 1.79; gap = 40.42%). All four channels had gaps of more than 34 per cent, however, indicating significant room for improvement in disseminating information, even in channels that perform relatively well.

The most shocking discovery was the very poor mean score (1.18) and the corresponding information transfer gap (60.76%) in the private sector and agri-input companies with the lowest rank among all five channels. This is a clear indication that the role of

Table 1. Statement-wise Information Transfer Level with Mean Score and Information Transfer Gap (%)

Item	Information Transfer	
	Mean	Gap %
Mass Media Exposure	1.79	40.42
Transfer by Personal Localite	1.96	34.61
Extension Contact	1.85	38.38
Extension Participation	1.91	36.48
Private Sector/Companies	1.18	60.76

Table 2. Evaluation Metrics of the Random Forest Model

Statement	R^2 Score	Mean Absolute Error (MAE)	Root Mean Squared Error (RMSE)	Mean Absolute Percentage Error (MAPE)
Training set performance	0.9159	0.7076	0.8816	0.0155
Test set performance	0.5943	1.3508	1.8077	0.0288
Full dataset performance	0.8604	0.8362	1.1293	0.0182

the private sector in the agricultural information system of tribal Malkangiri is negligible, due to the area's limited commercial potential and the purchasing power of tribal farming households.

Table 2 shows the evaluation indicators of the random forest (RF) regression model on training set, test set and full data set. The following four metrics were used to assess the models: coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE).

The model showed a good fit in the training set, with an R^2 of 0.9159, meaning that the model accounted for 91.59 per cent of the variance in the scores of agricultural information transfer during the learning phase. The MAE, RMSE, and MAPE were 0.7076, 0.8816, and 0.0155 (1.55%) respectively, which indicated that the average prediction error was still acceptable on training data.

On the test set, however, model performance declined noticeably, with R^2 dropping to 0.5943, MAE rising to 1.3508, RMSE to 1.8077, and MAPE to 0.0288 (2.88%). An R^2 value of 0.9159 when the model was trained, and 0.5943 when tested, indicates a substantial training–test gap... consistent with significant overfitting explains the mechanistic reason (14 predictors, n=120, max depth 10). This is a known limitation of tree-based ensemble methods when applied to relatively small datasets, as the 120-respondent sample used in the present study may be insufficient for the model to fully capture generalisable patterns without overfitting.

On the full dataset, the RF model achieved an intermediate R^2 of 0.8604, with MAE of 0.8362, RMSE of 1.1293, and MAPE of 0.0182 (1.82%), reflecting an overall moderate-to-good level of predictive accuracy when all 120 observations were included. Taken together, the evaluation metrics confirm that while the random forest model possesses strong learning capacity, its generalisation to new tribal farmer populations' remains moderate. These findings justify the complementary use of ridge regression, which recorded superior cross-validation R^2 (0.503) and offered greater interpretability for extension planning, as discussed subsequently.

Figure 1 shows the performance of the random forest (RF) model as tested on the three measures cross-validation R^2, mean absolute error (MAE), and root mean square error (RMSE) for five-fold cross-validation (CV).

Regarding cross validation R^2, the scores varied from a minimum of 0.2909 in Fold 5 to a maximum of 0.4837 in Fold 4 and the mean CV R^2 was 0.4282. Model learning was consistently the same for folds 1-4 with R^2 values between 0.4523 and 0.4837, showing that the model learned similar information across most of the data partitions. The depressed CV R^2 of 0.2909 in Fold 5 warrants explicit justification. With a total sample of only 120 respondents partitioned into five folds, each validation fold contains approximately 24 observations. Small fold sizes of this magnitude render CV R^2 estimates highly sensitive to the distributional composition of the withheld subset. This interpretation is corroborated by Fold 5's concurrent MAE of 1.4547 and RMSE of 1.8500–both the lowest recorded across all five folds confirming that the model's absolute prediction errors were actually smallest in this fold. The apparent paradox of low R^2 alongside low MAE/RMSE is therefore a statistical artefact of reduced outcome variance in the Fold 5 holdout, not evidence of model misspecification or localised instability.

The MAE scores across the five folds ranged from 1.4547 (Fold 5) to 1.8539 (Fold 2), with a mean MAE of 1.6921. Folds 1, 2, and 3 had MAE values higher than the mean (1.7993, 1.8539, and 1.7987, respectively) while Folds 4 and 5 were lower than the mean (1.5539 and 1.4547, respectively) showing that the model had smaller absolute prediction errors in the latter folds, but Fold 5 had the lowest value of R^2 (0.650). These seemingly conflicting results indicate that the model had relatively smaller absolute error in Fold 5, but its ability to explain the overall variance in the fold was limited, possibly because of limited range or fewer variability in the outcome variable in the fold.

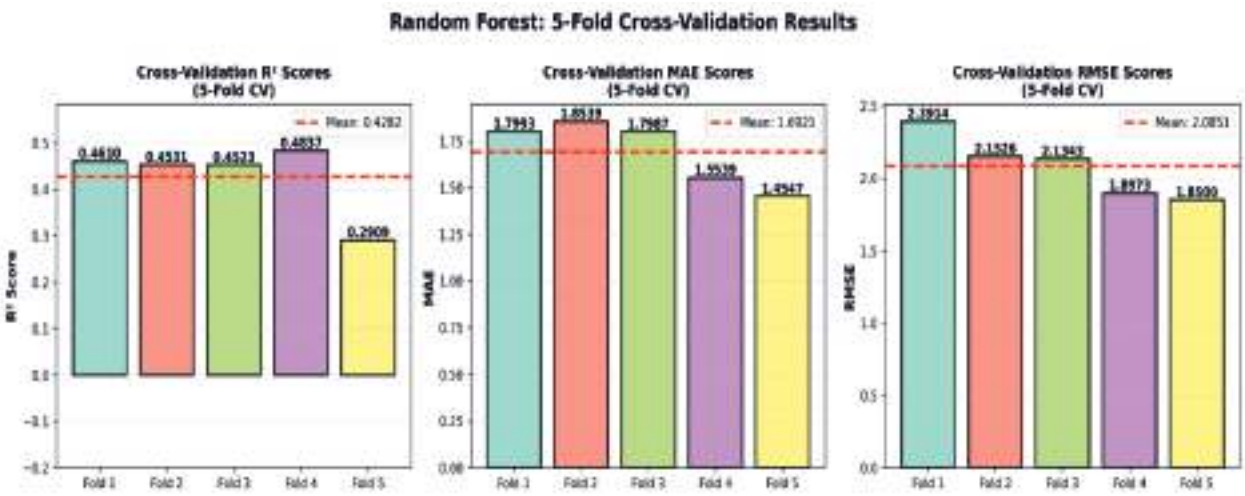


Figure 1. 5 Fold Cross Validation Scores

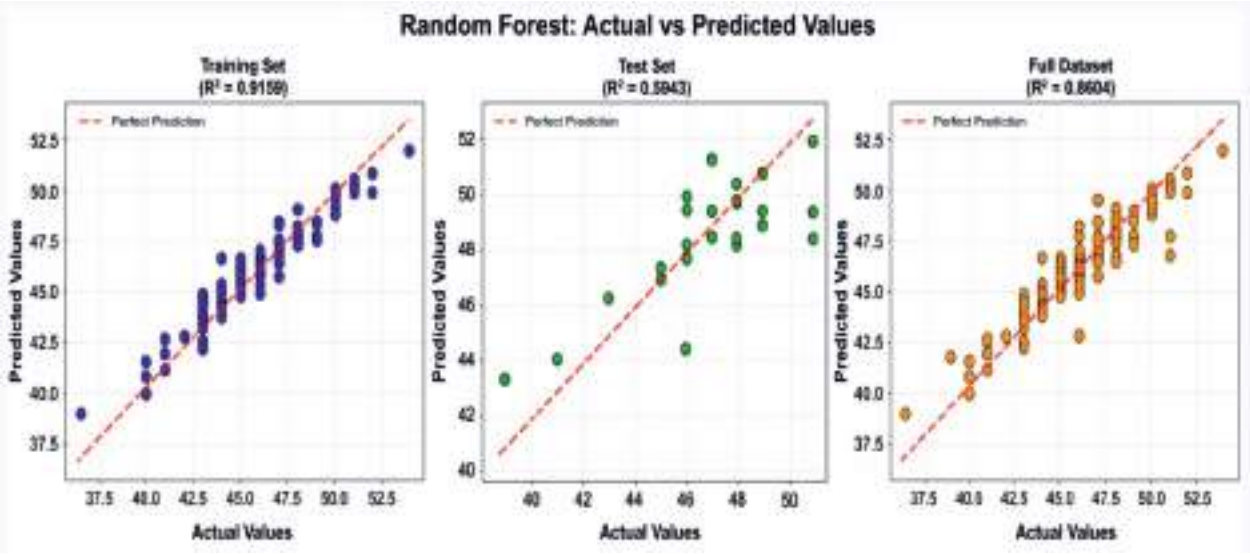


Figure 2. Actual vs Predicted

The RMSE values were generally similar, ranging from 2.3914 in Fold 1 to 1.8500 in Fold 5 and an average value of 2.0851. The Folds 4 and 5 recorded the lowest RMSE values (1.8973 and 1.8500 respectively), showing that the prediction errors produced in these partitions were relatively smaller when compared with Fold 1 which recorded the highest RMSE value of 2.5769.

Overall, the results of the cross validation confirmed the substantial to consistent generalisability of the RF model across all five folds, with mean CV R^2 (0.4282), mean MAE (1.6921), and mean RMSE (2.0851) all suggesting the RF model explained around 42.82 per cent of variance in the agricultural information transfer scores on unseen data, with the mean error in prediction being approximately 1.69 units. The CV R^2 was also relatively lower than the full data set R^2 (0.8604), which further supported the degree of overfitting that was seen in the Table 2.

The Figure 2 presents a comprehensive performance evaluation of a Random Forest regression model through actual versus predicted value scatter plots across three distinct data partitions, revealing critical insights into the model's predictive capabilities and generalization performance. The three-panel visualization employs a consistent format where the x-axis represents actual observed values and the y-axis shows model predictions, with a red dashed diagonal line indicating perfect prediction (where predicted values exactly equal actual values). The Training Set (left panel, blue points) exhibits remarkably strong performance with an R^2 of 0.9159, demonstrating that the model explains approximately 91.6% of the variance in the training data, with data points clustering tightly along the perfect prediction line across the entire range from approximately 37.5 to 52.5. This near-excellent fit suggests the Random Forest algorithm has effectively captured the underlying patterns and relationships within the training data. However, the Test Set (middle panel, green points) tells a dramatically different story, with R^2 plummeting to 0.5943, indicating that only about 59.4% of variance is explained when the model encounters previously unseen data. The substantially increased scatter from the perfect prediction line, particularly noticeable at the lower end of the actual value range (around 40-44), reveals systematic prediction errors and highlights the model's difficulty in generalizing beyond its training experience. Several conspicuous outliers appear where the model either significantly overestimates or underestimates actual values, suggesting the presence of complex patterns or feature interactions that the model failed to learn in a generalizable manner. The Full Dataset panel (right, orange points) combines both training and test observations, yielding an intermediate R^2 of 0.8604, which represents a weighted average performance across all data but masks the concerning performance discrepancy between training and testing phases. The stark 32-percentage-point drop in R^2 from training to test (0.9159 to 0.5943) is a classic signature of overfitting, where the model has essentially memorized noise and specific idiosyncrasies of the training data rather than learning truly generalizable relationships, causing it to perform poorly when faced with new observations that contain different random variations or slightly different patterns. This overfitting could stem from several potential issues: the Random Forest may have too many trees with insufficient regularization, the training set might be too small or unrepresentative of the broader population, important features may be missing that would help the model generalize, or there may be fundamental differences in the distributions between training and test sets that the model cannot bridge.

Figure 3 presents the feature importance scores of all 14 predictor variables derived from the random forest (RF) model, ranked in descending order of their relative contribution to predicting agricultural information transfer among tribal farmers of Malkangiri. Feature importance in the RF framework reflects the mean decrease in node impurity attributable to each variable across all decision trees in the ensemble, thereby providing a data-driven ranking of predictor variables independent of linear assumptions.

Farming experience emerged as the most influential predictor of agricultural information transfer, recording the highest importance score of 0.3680, which accounted for approximately 36.80 per cent of the total predictive contribution of the model. This finding indicated that the number of years a tribal farmer had been engaged in agricultural activities was the determinant of the extent to which agricultural information was transferred, suggesting that experiential

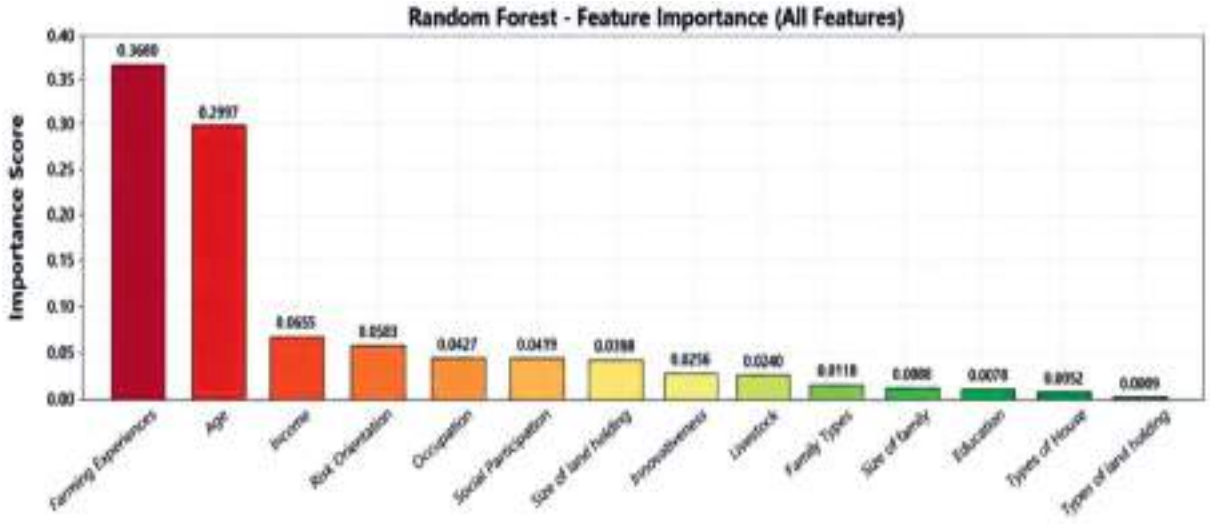


Figure 3. Feature Importance

learning accumulated over years of farming practice substantially enhanced a farmer's capacity to seek, process, and relay agricultural information within the community. Age ranked second in importance with a score of 0.2997 (29.97%), underscoring the combined dominance of farming experience and age, which together accounted for 66.77 per cent of the model's total feature importance.

The remaining 12 variables collectively contributed only 33.23 per cent of the total feature importance, highlighting the overwhelming dominance of farming experience and age in predicting information transfer. Among the remaining predictors, income ranked third with an importance score of 0.0655 (6.55%), followed by risk orientation (0.0583; 5.83%), occupation (0.0427; 4.27%), social participation (0.0419; 4.19%), and size of land holding (0.0398; 3.98%). These variables occupied an intermediate tier of importance, suggesting a secondary but non-negligible role in shaping the agricultural information transfer behaviour of tribal farmers. Innovativeness (0.0256) and livestock ownership (0.0240) contributed marginally to the model's predictive power, while family types (0.0118), size of family (0.0088), education (0.0078), and types of house (0.0052) recorded very low importance scores, indicating minimal independent influence on information transfer once the dominant variables were accounted for. Types of land holding recorded the lowest importance score of 0.0009, contributing less than 0.1 per cent to the model's overall predictive capacity, suggesting that the nature of land tenure had virtually no bearing on information transfer behaviour among the tribal farmers studied.

The colour gradient of the bars in Figure 3, transitioning from deep red for the highest-importance variables to yellow-green for the lowest, visually reinforced the sharp hierarchical differentiation among predictor variables. The steep decline in importance scores from farming experience (0.3680) and age (0.2997) to income (0.0655) and beyond reflected a highly skewed distribution of predictive contributions, a pattern consistent with earlier machine learning-based studies in agricultural extension research which reported that experiential. These results further validated the regression findings, wherein farming experience and age emerged as the two statistically significant predictors with the largest standardised coefficients in the multiple linear regression model.

The SHAP (SHapley Additive exPlanations) summary bee swarm plot for random forest model shows the direction, magnitude, and distribution of each predictor variable's contribution towards predicting agricultural information transfer among tribal farmers of Malkangiri district. One dot in the plot represented one farmer's observation, with the horizontal position of the dot corresponding to the magnitude and direction of its effect on the model's prediction for that observation, or the SHAP value. Dots placed to the right of the zero baseline indicated a positive effect on predicted information transfer scores, and dots placed to the left indicated a negative effect on predicted information transfer scores. Each dot was colour-coded with the value of the feature associated with the observation, and this colour code of the dots allowed the direction of effect to be interpreted along with the nature of the feature value causing the effect.

The farming experience variable showed the greatest horizontal range in SHAP values of any of the 14 variables, ranging from around –4.0 on the negative side to well beyond +3.0 on the positive side, indicating its importance as a predictor in the model. The direction of the colour pattern for farming experience showed a clear, consistent pattern: dots with higher farming experience values were predominantly on the positive side of the baseline, suggesting that increased farming experience significantly increased farmers' predicted information transfer scores. On the other hand, low farming experience farmers (blue dots) were placed on the negative side which suggested that their limited experience resulted in lower predicted scores.

Age also showed a similar pattern, with an increasing number of red dots located to the right of the zero line and blue dots to the left of the zero line indicating a consistent positive relationship between older age and greater predicted information transfer. SHAP values for age ranged from around –3.0 to above +2.5 indicating that age is the second most influential variable, and in line with the feature importance results shown in Figure 3.

Income showed a rather different picture, with red points representing the high income farmers concentrated on the negative side of the baseline and blue points representing the low-income farmers on the positive side. The inverse relationship suggests that

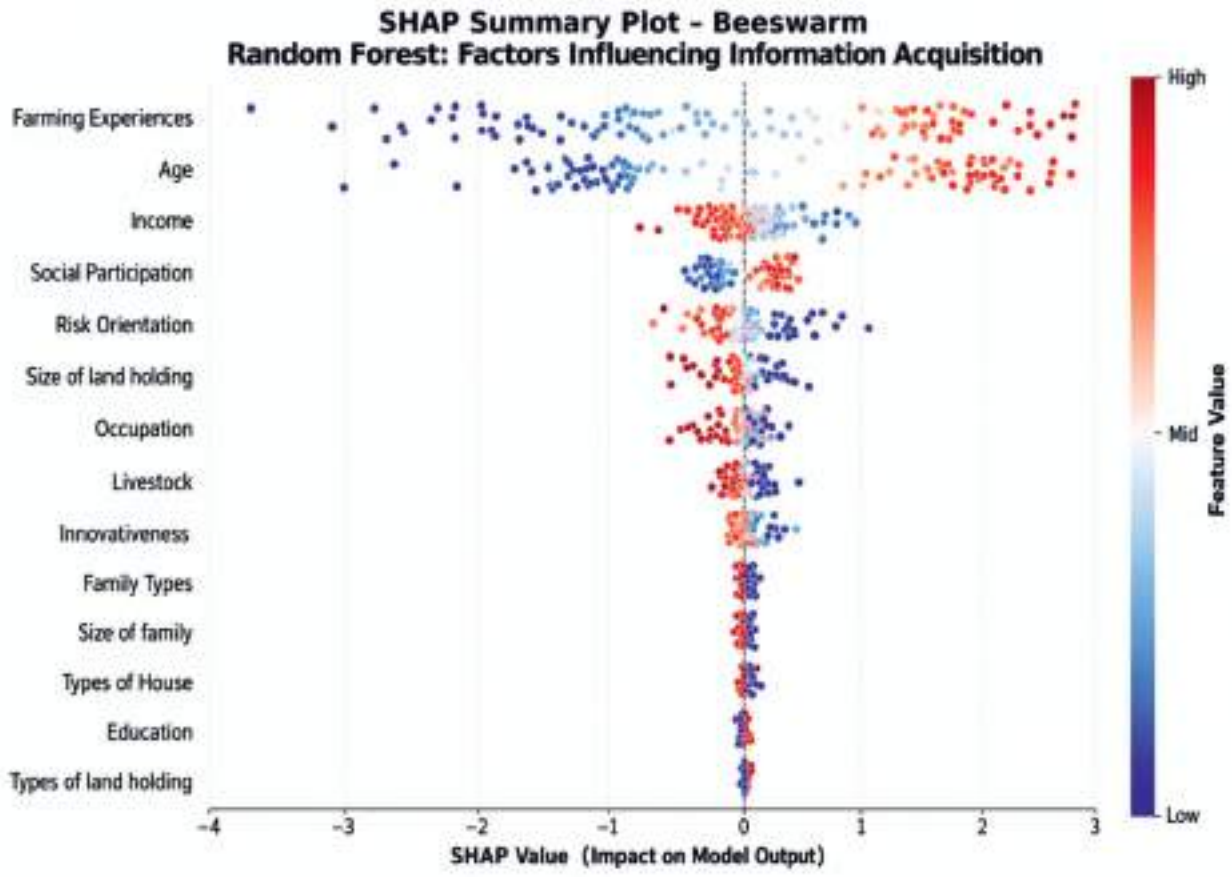


Figure 4. SHAP Summary Plot

a higher income level was correlated with lower predicted information transfer scores, which implies that wealthier tribal farmers may be less dependent on community-based or extension mediated sources of information and may get agricultural information from private or commercial sources. The direction of social participation showed clear positive data with a majority of observations (red dots) to the right of zero, indicating that higher levels of social participation facilitated greater information transfer. The data of the risk orientation presented a mixed distributional pattern, with high and low feature values being found on each side of the baseline, suggesting a more complex non-linear relationship between risk orientation and information transfer, which may not have been adequately captured by simple regression coefficients.

All the remaining variables, with the exception of innovativeness and size of family, had small SHAP value ranges close to the SHAP baseline of zero and the dots of all observations were tightly grouped around zero. This pattern indicates that these variables had relatively low and inconsistent contributions to the prediction of agricultural information transfer across the range of observed values. Education had a significantly smaller spread than the other lower-tier variables, with the shapes of most observations falling within a range of SHAP values from –0.5 to +0.5.

DISCUSSION

The findings of the present study reveal that agricultural information transfer among tribal farmers of Malkangiri is low to moderate across all five channels, with personal localite contacts recording the highest mean score (1.96) and the smallest information transfer gap (34.61%), while private sector and agri-input companies register the most critical deficiency (mean = 1.18; gap = 60.76%). This pattern aligns with Rajkhowa and Qaim (2021) and Coggins et al. (2022), who establish that geographically isolated and socially marginalised farming communities depend predominantly on informal interpersonal networks rather than formal or market-mediated channels for agricultural information, owing to structural barriers such as sparse extension coverage, linguistic diversity, and limited digital access. The finding corroborates Jat et al. (2021), who similarly documented that tribal farmers in backward districts of India rely on community-based contacts as their primary information source.

Farming experience emerges as the single most influential determinant of agricultural information transfer, accounting for 36.80 per cent of the random forest model's predictive contribution, with SHAP values confirming a consistent positive directional effect across all 120 observations. Age contributes an additional 29.97 per cent, and together these two variables explain 66.77 per cent of the model's total feature importance. Income presents an inverse relationship with information transfer, wherein high-income farmers are associated with negative SHAP values, indicating a suppressive effect on predicted scores. This counterintuitive finding agrees with Rajkhowa and Qaim (2021), who report that higher-income smallholder farmers substitute public extension information with

market-mediated advisory services, reducing their engagement with community-based channels. Social participation (importance = 0.0419) displays a consistent positive SHAP direction, validating the argument of Begho (2025) and Lai (2025) that collective institutional engagement through farmer networks enhances information access and relay capacity. Risk orientation presents a non-linear, mixed directional pattern, suggesting its effect is substantial by contextual variables such as income and experience - a nuance that linear regression alone cannot reveal.

CONCLUSION

The study reveals that the farming experience and age were the two key factors affecting agricultural information transfer among the tribal farmers of Malkangiri, with almost two-thirds of the total predictive power of the model, whereas income, social participation and risk orientation had a secondary impact. Private sector involvement is still underutilised, while personal locality contacts are the most effective channel of information. This is because the machine learning method used in the study has high learning ability, while its generalisation ability is substantial, which underscores the importance of an interpretable regularised regression method for designing extension programmes. Targeted extension strategies that prioritise experienced and older farmers as community information leaders, strengthen farmer group participation, and diversify channel outreach beyond informal networks are essential for bridging the persistent information transfer gap in tribal Malkangiri.

DECLARATIONS

Ethics approval and informed consent: The respondents were asked for their informed consent.

Conflict of interest: The research was carried out without any financial or commercial ties that might be seen as a potential conflict of interest, according to the authors. The authors affirm that they carefully examined, amended and edited the content as necessary when preparing this work. The final content of this publication is entirely the authors' responsibility.

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Research Article

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Family Resources and Agricultural Skills as determinants of Farmer's Motivation in Rubber Cultivation in Kerala

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HIGHLIGHTS

- Family resources strongly impact the economic and risk–stability motivation in rubber farming.
- Risk-stability motivation is negatively influenced by the agricultural skill, indicating a low level of perceived risk.
- Except for gender, impact on adoption of rubber farming has minimal effect by socio-economic factors.
- Policy should target resource access and skill translation into adoption behaviour.

ARTICLE INFO

Keywords: Agricultural skill, Economic motivation, Kerala, Resource access, Rubber cultivation, Risk-stability motivation.

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ABSTRACT

The research analysed the factors affecting the motivation for rubber cultivation among 180 smallholder farmers in Kerala during 2025. The study was based on primary data collected from 180 farmers and data were analysed using Pearson correlation and hierarchical multiple regression. Results indicate that farmers demonstrated moderate-to-high motivation for rubber cultivation, with economic motivation averaging 3.73, whereas risk–stability motivation reflected a mean of 3.87 on a five-point scale. The resource ownership and control index appeared as the strongest indicator, having an appositive impact on both motivational dimensions, while the financial and institutional access index affected economic motivation only. Agricultural skills have a negative association with risk–stability motivation, suggesting skilled farmers are involved in rubber cultivation due to low perceived risk. Socio-demographic characteristics had limited impact, except gender, which affects economic motivation. The findings suggest that family resource access is the major driver of motivational outcome, whereas skill and demographic factors have limited roles. Policy interventions improving the resource access and converting skill into informed decision-making can strengthen sustainable and economically viable rubber cultivation.

INTRODUCTION

Natural rubber is a commercial plantation crop in tropical agricultural economies due to its high industrial demand and export potential. In India, rubber cultivation forms an integral component of smallholder farming in regions having fragmented landholdings and labour-intensive production structures (Gordon, 2019).

Kerala remains as the major centre of rubber cultivation in India, accounting for the largest share of the country's area and production. The state has approximately 3.84 lakh hectares under rubber cultivation and contributes more than half of India's natural rubber output (Rubber Board of India, 2024). Further, this sector is mainly dominated by smallholders, with holdings below two hectares. That is, rubber cultivation supports the livelihoods of a large number of rural households and create employment through production, processing, and marketing activities. However, the sector has undergone considerable changes in the recent times due to price volatility, rising labour costs, increasing production expenses, climate-related challenges, and changing market conditions (Sahadevan & Vaithiyanathan, 2025). These developments have influenced farmers' perceptions of profitability and changed their crop preference decisions making the understanding of determinants

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of rubber cultivation preference increasingly important in Kerala's smallholder-dominated plantation economy. Identifying the factors that influence farmers' preference for rubber cultivation remains important for agricultural planning, resource allocation, and rural livelihood sustainability (Vishnuprathap et al., 2024).

Although previous studies have mainly focused on the profitability, production, and marketing factors of plantation crops, limited attention has been given to the role of household resources and agricultural skills in shaping farmers' cultivation preferences. This gap is particularly relevant in the context of rubber cultivation, which requires substantial initial investment, specialised management capabilities, and the capacity to sustain production despite delayed returns. Consequently, both household resource endowments and human capital characteristics are likely to influence farmers' cultivation decisions. Moreover, empirical studies that examine the dimensional structure of agricultural skills, resource access, and motivational factors, while simultaneously developing validated composite indices and assessing their effects on cultivation preference after controlling for socio-demographic characteristics, remain scarce. Therefore, this study hypothesises that family resource access and agricultural skills significantly influence farmers' preference for rubber cultivation, while socio-demographic characteristics also contribute to preference formation. By integrating household capital theory and human capital perspectives and employing psychometric validation together with multivariate regression analysis, the study provides a comprehensive framework for understanding the determinants of farmers' preference for rubber cultivation.

METHODOLOGY

The present study is conducted in the Palakkad district of Kerala, by considering two major panchayats where rubber farming is prevalent, Nenmara and Thiruvazhiyode. A field-based, cross-sectional research design was adopted. Data were collected from 180 rubber farmers mainly through personal interviews employing a structured interview schedule during 2024–2025. The interview schedule is divided into socio-demographic variables (gender, family type, marital status, landholding size, and farming experience); eight statements measuring agricultural skills; nine statements evaluating resource access and control; and ten statements examining reasons for rubber cultivation. All given items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Landholding size was recorded in cents (1 cent = 40.47 m^2).

Reliability of the items was assessed using Cronbach's alpha (α). It was revealed that agricultural skill scale has $\alpha = 0.798$, the resource access, $\alpha = 0.791$, and the reasons for rubber cultivation scale, $\alpha = 0.819$, reflecting an overall satisfactory reliability ($\alpha \geq 0.70$) (Nunnally, 1978). Construct validity was evaluated by conducting exploratory factor analysis applying principal component analysis with Varimax rotation after checking the sample adequacy tests. The Kaiser–Meyer–Olkin statistic values for resource access (0.826), agricultural skill (0.826), and reasons for rubber cultivation (0.849) indicate sampling adequacy. Bartlett's Test of Sphericity was statistically significant for all constructs ($p < 0.001$), confirming that the correlation matrices were not identity matrices and were suitable for factor extraction (Kaiser, 1974). Based on the extraction, two factors were formed under each resource access and for reasons for rubber cultivation were created.

Composite indices were constructed by calculating the average of items under each extracted factor, resulting in the Agricultural Skill Index, Resource Ownership and Control Index, Financial and Institutional Access Index, Economic Motivation Index, and Risk–Stability Motivation Index. Since the dependent variables, namely the Economic Motivation Index and Risk–Stability Motivation Index, are continuous composite measures derived from multiple Likert-scale items, multiple linear regression analysis was employed to examine the influence of agricultural skills, resource dimensions, and socio-demographic characteristics on farmers' motivational outcomes. The model is expressed as follows.

$$Yi = \beta_o + \beta_1 Si + \beta_2 Ri + \beta_3 Gi + \beta_4 Fi + \beta_5 Li + \beta_6 Ei + \beta_7 Mi + \varepsilon i \quad ...(1)$$

$$Yj = \beta_o + \beta_1 Si + \beta_2 Ri + \beta_3 Gi + \beta_4 Fi + \beta_5 Li + \beta_6 Ei + \beta_7 Mi + \varepsilon i \quad ...(2)$$

where Yi represented economic motivation; Yj denoted risk stability motivation; Si indicated the agricultural skill index; Ri denoted resource-related indices; Gi showed gender; Fi represented family type; Li denoted landholding size (cents); Ei indicated farming experience (years); Mi represented marital status; β_o was the intercept; β_1–β_7 were regression coefficients; and ε_i was the random error term.

RESULTS

Descriptive statistics

Farmers reported moderate to high levels of motivation, with economic motivation averaging 3.73 and risk–stability motivation 3.87, reflecting both profit-driven and risk-conscious behaviours. Resource access emerged as a significant factor, with households having substantial ownership and control over productive assets (M = 3.80) and also financial and institutional access (M = 3.88). Agricultural skills were moderate (M = 2.03), indicating that though the farmers possess basic technical and managerial competencies, there is need for improvement in activities where they are involved, such as tapping advanced cultivation practices, risk management, and productivity enhancement.

Table 1. Descriptive Statistics of Indices

Indices	Mean	Std. Deviation	N
Economic and Institutional Motivation	3.7300	.70544	180
Risk and Stability Motivation	3.8741	.77288	180
Agricultural Skill Index	2.0319	.67232	180
Resource Ownership and Control	3.8019	.66638	180
Financial and Institutional Access	3.8778	.66564	180

Determinants of economic motivation

Hierarchical multiple regression analysis was applied for identifying the key factor affecting the economic motivation. Table 2 give the model summary. Agricultural Skill Index, Resource Ownership and Control, and Financial and Institutional Access were incorporated in the first model, and the model explained 43.5% of the variance ($R^2 = 0.435$) and was statistically significant. The

ANOVA results in Table 3 further confirm the overall significance of the model. As Table 4 states that resource Ownership and Control has the strongest impact (β = 0.528, p < 0.001), followed by Financial and Institutional Access (β = 0.186, p = 0.010), indicating the significance of resource access in motivating to adopt the plantation crop, like rubber. The agricultural skill index did not significantly affect the economic motivation (β = -0.009, p = 0.898).

With the inclusion of socio-demographic variables in Model 2 (Table 2), the explanatory power of the model increased marginally from 43.5 per cent to 46.6 per cent (R^2 = 0.466). However, the R^2 change of 0.031 was not statistically significant (F change = 1.999, p = 0.081), indicating that demographic variables contributed little additional explanatory value beyond resource-based factors. As observed in Table 4, Resource Ownership and Control (β = 0.519, p < 0.001) and Financial and Institutional Access (β = 0.205, p = 0.006) remained significant predictors even after controlling for demographic characteristics. Among the newly added variables, only Gender showed a significant positive effect (β = 0.120, p = 0.038), whereas Experience, Marital Status, Type of Family, and Area under Cultivation were statistically non-significant. The collinearity

Table 2. Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.659[a]	.435	.425	.53496	.435	45.089	3	176	.000
2	.682[b]	.466	.441	.52752	.031	1.999	5	171	.081

a. Predictors: (Constant), Financial and Institutional Access, Agricultural Skill Index, Resource Ownership and Control, b. Predictors: (Constant), Financial and Institutional Access, Agricultural Skill Index, Resource Ownership and Control, Experience in Rubber Farming, Type of family, Marital Status of the respondent, Gender, Area under cultivation, c. Dependent Variable: Economic and Institutional Motivation, R = Multiple Correlation Coefficient; R^2 (R Square) = Coefficient of Determination; Adjusted R^2 = Adjusted Coefficient of Determination; df = Degrees of Freedom; Sig. = Significance Level.

Table 3. ANOVA[a] Results

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	38.710	3	12.903	45.089	.000[b]
	Residual	50.368	176	.286		
	Total	89.078	179			
2	Regression	41.492	8	5.187	18.638	.000[c]
	Residual	47.586	171	.278		
	Total	89.078	179			

a. Dependent Variable: Economic and Institutional Motivation, b. Predictors: (Constant), Financial and Institutional Access, Agricultural Skill Index, Resource Ownership and Control, c. Predictors: (Constant), Financial and Institutional Access, Agricultural Skill Index, Resource Ownership and Control, Experience in Rubber Farming, Type of family, Marital Status of the respondent, Gender, Area under cultivation, ANOVA = Analysis of Variance; df = Degrees of Freedom; Sig. = Significance Level.

Table 4. Hierarchical Multiple Regression analysis for Economic Motivation

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	.859	.406		2.116	.036					
	Agricultural Skill Index	-.009	.071	-.009	-.129	.898	-.366	-.010	-.007	.701	1.427
	Resource Ownership and Control	.559	.080	.528	7.019	.000	.641	.468	.398	.567	1.764
	Financial and Institutional Access	.197	.075	.186	2.617	.010	.498	.194	.148	.638	1.568
2	(Constant)	.057	.480		.119	.906					
	Agricultural Skill Index	-.004	.072	-.003	-.050	.960	-.366	-.004	-.003	.669	1.495
	Resource Ownership and Control	.550	.080	.519	6.905	.000	.641	.467	.386	.553	1.809
	Financial and Institutional Access	.218	.078	.205	2.807	.006	.498	.210	.157	.583	1.715
	Gender	.185	.089	.120	2.086	.038	.052	.158	.117	.938	1.066
	Experience in Rubber Farming	.047	.031	.086	1.505	.134	.116	.114	.084	.966	1.035
	Marital Status of the respondent	.104	.103	.058	1.012	.313	.116	.077	.057	.957	1.045
	Type of family	.032	.090	.020	.357	.721	.083	.027	.020	.954	1.048
	Area under cultivation	.093	.062	.088	1.501	.135	.053	.114	.084	.901	1.110

a. Dependent Variable: Economic and Institutional Motivation, B = Unstandardized Regression Coefficient; Beta (β) = Standardized Regression Coefficient; Sig. = Significance Probability (p-value); VIF = Variance Inflation Factor.

statistics (VIF values below 2) indicate absence of multicollinearity issues.

Determinants of risk–stability motivation

The hierarchical multiple regression results presented in Table 5, 6 and 7 explain the determinants of Risk and Stability Motivation among rubber farmers. As shown in 5, Model 1, including the Resource Ownership and Control, Financial and Institutional Access, and Agricultural Skill Index, was statistically significant ($F = 31.700$, $p < 0.001$) and 35.1 per cent of the variation in risk–stability motivation ($R^2 = 0.351$; Adjusted $R^2 = 0.340$) were explained. The ANOVA results in Table 6 further confirm the overall model significance. The regression coefficients in Table 6 indicate that Agricultural Skill Index had a significant negative effect ($\beta = -0.318$, $p < 0.001$), suggesting that higher skill levels are associated with lower dependence on risk–stability motivation, possibly due to greater confidence and diversification capacity. Resource Ownership and Control exerted a positive and significant influence ($\beta = 0.304$, $p < 0.001$), indicating that farmers with stronger asset control perceive rubber cultivation as a relatively stable livelihood option. However, Financial and Institutional Access was not statistically significant in Model 1 ($\beta = 0.079$, $p = 0.300$).

With the inclusion of socio-demographic variables in Model 2 (Table 5), the explanatory power increased marginally from 35.1 per cent to 37.1 per cent ($R^2 = 0.371$). Nevertheless, the R^2 change of 0.020 was statistically non-significant (F change = 1.114, $p = 0.355$), implying that demographic factors added limited explanatory value beyond resource-based variables. As observed in Table 7, Agricultural Skill Index ($\beta = -0.344$, $p < 0.001$) and Resource Ownership and Control ($\beta = 0.329$, $p < 0.001$) remained robust predictors even after controlling for demographic characteristics. Among the newly introduced variables, only Area under Cultivation showed a significant negative association ($\beta = -0.138$, $p = 0.033$), indicating that farmers with larger cultivated areas may exhibit relatively lower risk–stability motivation, possibly due to scale advantages or diversified risk management strategies. Gender, Experience, Marital Status, and Type of Family were statistically non-significant.

Multicollinearity and model diagnostics

Variance inflation factors (Table 7) for all predictors were below 5, suggesting that multicollinearity was not a concern. Residuals were normally distributed, and observed versus predicted values fell within acceptable ranges, further confirming the adequacy of the regression models.

DISCUSSION

The findings of the present study establish that household resource endowments–particularly ownership and control over resources and access to financial and institutional support–are the principal determinants of both economic motivation and risk–stability motivation among smallholder rubber farmers in Palakkad district. This aligns strongly with the Sustainable Livelihoods Framework, which posits that livelihood strategies are fundamentally shaped by access to capital assets–natural, financial, physical, human, and social–rather than by demographic attributes alone (Wang et al., 2023; Feder et al., 1985). In the context of plantation crops such as rubber, which require long gestation periods, sustained capital investment, and tolerance for delayed returns, resource access becomes not merely supportive but structurally decisive.

Table 5. Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.592[a]	.351	.340	.62802	.351	31.700	3	176	.000
2	.609[b]	.371	.342	.62701	.020	1.114	5	171	.355

a. Predictors: (Constant), Financial and Institutional Access, Agricultural Skill Index, Resource Ownership and Control, b. Predictors: (Constant), Financial and Institutional Access, Agricultural Skill Index, Resource Ownership and Control, Experience in Rubber Farming, Type of family, Marital Status of the respondent, Gender, Area under cultivation, c. Dependent Variable: Risk and Stability Motivation, R = Multiple Correlation Coefficient; R^2 (R Square) = Coefficient of Determination; Adjusted R^2 = Adjusted Coefficient of Determination; df = Degrees of Freedom; Sig. = Significance Level.

Table 6. ANOVA[a] Results

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	37.508	3	12.503	31.700	.000[b]
	Residual	69.415	176	.394		
	Total	106.923	179			
2	Regression	39.697	8	4.962	12.622	.000[c]
	Residual	67.226	171	.393		
	Total	106.923	179			

a. Dependent Variable: Risk and Stability Motivation, b. Predictors: (Constant), Financial and Institutional Access, Agricultural Skill Index, Resource Ownership and Control, c. Predictors: (Constant), Financial and Institutional Access, Agricultural Skill Index, Resource Ownership and Control, Experience in Rubber Farming, Type of family, Marital Status of the respondent, Gender, Area under cultivation, ANOVA = Analysis of Variance; df = Degrees of Freedom; Sig. = Significance Level.

Table 7. Hierarchical Multiple Regression analysis for Risk and Stability Motivation

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	2.919	.477		6.125	.000					
	Agricultural Skill Index	-.365	.083	-.318	-4.377	.000	-.511	-.313	-.266	.701	1.427
	Resource Ownership and Control	.353	.094	.304	3.771	.000	.517	.273	.229	.567	1.764
	Financial and Institutional Access	.092	.088	.079	1.039	.300	.393	.078	.063	.638	1.568
2	(Constant)	3.332	.570		5.841	.000					
	Agricultural Skill Index	-.396	.085	-.344	-4.643	.000	-.511	-.335	-.282	.669	1.495
	Resource Ownership and Control	.382	.095	.329	4.038	.000	.517	.295	.245	.553	1.809
	Financial and Institutional Access	.037	.092	.032	.401	.689	.393	.031	.024	.583	1.715
	Gender	.040	.105	.024	.378	.706	-.060	.029	.023	.938	1.066
	Experience in Rubber Farming	.015	.037	.026	.416	.678	.069	.032	.025	.966	1.035
	Marital Status of the respondent	-.075	.122	-.038	-.613	.540	.022	-.047	-.037	.957	1.045
	Type of family	-.061	.107	-.035	-.570	.570	-.006	-.044	-.035	.954	1.048
	Area under cultivation	-.159	.074	-.138	-2.153	.033	-.092	-.162	-.131	.901	1.110

Dependent Variable: Risk and Stability Motivation

The positive association between resource access and economic motivation confirms that smallholders with stronger asset bases are more inclined to engage in commercially oriented crops that yield returns over extended periods (Suriansyah et al., 2024; Ravi et al., 2026) Resource ownership functions as a stabilizing mechanism, enabling farmers to allocate land, mobilize labour, and absorb initial establishment costs despite uncertainty. Similarly, financial and institutional access enhances economic motivation by lowering credit constraints and facilitating integration with formal markets, consistent with evidence that innovation and adoption behaviour are strongly conditioned by economic capacity and institutional backing (Kassie et al., 2013; Nain et al., 2019; Gowda et al., 2022; Nain et al., 2024). These findings reinforce livelihood scholarship emphasizing that production decisions are embedded in material capability structures rather than purely attitudinal preferences (Wang et al., 2023).

A notable contribution of this study lies in the differentiated role of financial and institutional access across motivational dimensions. While such access significantly predicts economic motivation, it does not significantly explain risk–stability motivation. This suggests that formal institutional mechanisms may stimulate profit orientation without sufficiently altering subjective perceptions of long-term security. As observed in related studies, institutional support systems often address liquidity and market barriers but may inadequately engage with farmers' deeper perceptions of production risk and livelihood stability (Suriansyah et al., 2024). This distinction indicates that enhancing resilience requires not only financial inclusion but also risk mitigation instruments such as crop insurance, extension advisory systems, and long-term price stabilization measures.

The negative relationship between agricultural skill and risk–stability motivation presents an important theoretical nuance. Conventional human capital theory predicts that higher technical skill enhances motivation toward adoption and commercial agriculture. However, the present findings diverge from this expectation. Higher agricultural skill is associated with lower stability-oriented motivation, suggesting that skilled farmers may perceive themselves as more capable of managing uncertainty and therefore less dependent on stability-seeking motives. This interpretation resonates with psychological frameworks indicating that confidence can reduce perceived vulnerability and alter risk appraisal (Pathak, 1992; Suriansyah et al., 2024). Rather than uniformly increasing motivation, human capital appears to reshape motivational orientation by influencing subjective risk perception. This finding refines human capital assumptions by demonstrating that skill interacts with confidence and perceived control rather than directly amplifying risk-averse behaviour.

Socio-demographic characteristics exerted limited influence once structural variables were introduced. With the exception of gender in explaining economic motivation, variables such as marital status, family type, experience, and area under cultivation did not significantly shape motivational outcomes. The positive gender coefficient is consistent with literature documenting gender-based disparities in asset ownership, financial access, and decision-making authority (Wang et al., 2023). Male farmers' higher economic motivation likely reflects structural control over productive resources rather than inherent behavioural differences. The weak explanatory power of other demographic variables corroborates findings in plantation crop studies where demographic proxies lose significance when resource endowments are explicitly modeled (Mutyasira et al., 2018). This contrasts with consumer behaviour research, where socio-demographic factors strongly predict preference patterns (Vattekkad et al., 2025), thereby underscoring that production decisions in agriculture are materially constrained rather than socially stylized.

The overall pattern–strong resource effects, modest demographic effects, and an inverse association between skill and risk–stability motivation–reveals a complex motivational architecture among rubber smallholders. Farmers' motivational orientations are shaped by the interaction between objective resource portfolios and subjective perceptions of control. Where resources are abundant, both economic and stability motives are

reinforced. Where skill levels are high but resource endowments are limited, confidence may reduce stability-seeking orientation without necessarily enhancing structural security. This supports broader evidence that access to assets fundamentally alters how rational farmers perceive and respond to risk–return trade-offs in plantation agriculture (Wang et al., 2023).

In conclusion, the study confirms prior research highlighting the centrality of resource assets in shaping crop choice and motivational behaviour (Wang et al., 2023; Nain et al., 2024), while extending the literature by demonstrating that human capital, in the form of agricultural skill, and exerts a psychologically mediated influence rather than a uniformly positive effect. The findings call for future research examining the intersection of resource access, risk perception, institutional trust, and confidence in determining smallholder crop decisions. Policy interventions aiming to strengthen rubber cultivation should therefore prioritize asset enhancement and institutional depth alongside behavioural risk-management support to sustainably influence motivational orientation.

CONCLUSION

This study indicates that the main factors influencing farmers' motivation to cultivate rubber are household resource endowments. Both economic and risk-stability incentives are frequently driven by ownership and control over productive assets, and institutional and financial access further increases economic-oriented decisions. Agricultural skill shapes risk perception, with more skilled farmers having lower reliance on stability-driven strategies, indicating a shift to opportunity-focused and better-return behaviour. The findings further suggest that enhancing farmers' resource availability, strengthening institutional support mechanisms, and improving technical knowledge can play a crucial role in sustaining farmer motivation and promoting the long-term viability of rubber cultivation in Kerala.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the respondents of the study and their organizations during the course of the research.

Conflict of interest: The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Research Article

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Sectoral Ego and Data Integration Performance in an Extension Communication Perspective

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HIGHLIGHTS

- Conflict and abuse of authority weakened innovation diffusion performance
- Non-compliance unexpectedly supported quality, responsiveness, cooperation, and agility
- Distrust strengthened defensive coordination but weakened collaborative readiness
- Sectoral ego acted as a barrier to extension communication
- Innovation diffusion required adaptation, trust-building, and collaborative learning

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ABSTRACT

The study examined how sectoral ego shaped innovation diffusion performance within the Indonesia One Data Forum across ten provinces. Drawing on an extension communication perspective, the study aimed to explain the paradoxical effects of sectoral ego on organisational performance in implementing integrated development data governance. A quantitative descriptive design combined with path coefficient analysis was employed using data collected from March to August 2025 from 415 forum members selected through multistage random sampling. The findings showed that sectoral ego did not uniformly produce negative effects on organisational performance. Conflict and abuse of authority negatively affected quality, efficiency, cooperation, agility, and timeliness, indicating that communication barriers constrained innovation diffusion and collaborative performance. In contrast, non-compliance and distrust positively influenced quality, responsiveness, cooperation, and agility, suggesting the emergence of adaptive leaning and informal coordination within bureaucratic systems. The findings further revealed that high responsiveness was not accompanied by strong cross-sector cooperation, indicating that communication alone was insufficient to support innovation adoption. The study concluded that innovation diffusion depends not only on formal coordination mechanisms but also on behavioural adaptation, trust-building, and collaborative learning. Extension communication therefore provides a useful framework for strengthening collaborative readiness and supporting sustainable data integration initiatives.

INTRODUCTION

In data-driven development, the successful implementation of digital transformation policies is determined not only by the availability of technology, regulations, and infrastructure, but also by the effectiveness of communication and extension mechanism (Godara et al., 2024a; Godara et al., 2024b; Tommy et al., 2025). The extension communication perspective places significant emphasis on learning, knowledge exchange, and behavioural adaptation in supporting the adoption of innovation and

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organisational transformation (Salam et al., 2024). The diffusion of innovation is contingent on communicative processes that foster trust, collective commitment, and coordination between organisations (Everett, 2003; Putra & Pedersen, 2018).

A paucity of trust and collective commitment within the Indonesia One Data Forum (IODF) has impeded the management of development data. The number of regional IODF that have integrated their data in portal (https://data.go.id/), in 2024, remains below 50% of the total 514. IODF constitutes a collaborative governance mechanism that has been established in accordance with Presidential Regulation No. 39 of 2019. This forum serves as a platform for knowledge exchange, the dissemination of data standards and interoperability, and the facilitation of organisational learning. Conceptually, the IODF represents a form of organisational innovation diffusion within bureaucratic systems, with the potential to encourage organisations to change the way development data is managed and exchanged (Fan & Pan, 2023). The IODF acts as an agent of change driving innovation adoption, institutional adaptation, cross-organisational collaboration, and supports collaborative problem-solving. Nevertheless, the implementation process continues to encounter obstacles related to communication and collaborative readiness amongst organisations (Bernot et al., 2024).

One of the main challenges in IODF is sectoral ego, which refers to the tendency of organisations to prioritise institutional interests and authority over collective governance objectives (Islami, 2021). This phenomenon is reflected in the reluctance to share data, weak compliance with common standards, institutional competition, and resistance to cross-sectoral coordination mechanisms (Nurahmani, 2024a). Sectoral ego reflects incomplete organisational behavioural change in accepting data integration as a collective necessity (Jacob et al., 2024). Consequently, the formulation of development policies in Indonesia has not been sufficiently targeted; for instance, disputes over village discrepancies in geospatial data, the misallocation of health care aid, and inconsistent mortality data have resulted in discrepancies in the number of voters in general election (Ardani & Cahyani, 2022; Fajriyansyah & Apriani, 2024; Wayudi & Mukhlisun, 2020).

Studies predominantly conceptualise collaborative governance, extension communication, and the diffusion of innovation as separate analytical domains (Yigzaw, 2021). The majority of studies on extension communication continue to adopt approaches that are designed to modify the behaviour of individuals working within the agriculture and health sectors (Strayer et al., 2020; Chaturvedi & Vatta, 2026). Based on these gaps, the present study analyses the influence of sectoral ego on the data integration performance of the IODF. Theoretically, the study extends the application of extension communication in digital data governance by explaining the influence of communication barriers on innovation diffusion performance. Practically, the research findings are expected to support the strengthening of extension communication strategies to reinforce sustainable cross-sectoral data collaboration.

METHODOLOGY

The study was conducted between March and August 2025 within the Indonesia One Data Forum (IODF) across 10 of Indonesia's 38 provinces. The selected provinces represented the highest-performing regions in implementing data integration innovation according to the 2024 IODF Implementation Index (Secretariat of Indonesia One Data, 2024). Provincial performance was assessed based on the number of integrated datasets, metadata availability, data standardisation, interoperability, and data-sharing practices.

The sample size was determined using Slovin's formula with a 5% margin of error, resulting in a minimum of 400 respondents from a population of 7,742 IODF members. A multistage sampling approach was applied across three institutional levels. Stage 1: included all six National IODF members. Stage 2: included all 60 Provincial IODF members from the selected provinces. A census approach was used at both levels because of their relatively small populations. Stage 3: allocated the remaining sample (n = 334) proportionally across Regency/Municipal IODF using (n_i=(N_i/N)xn), where (N_i) represents the number of regencies/municipalities in each province and (N) the total across the ten provinces. Respondents at the Regency/Municipal level were then selected through random sampling.

The independent variable, sectoral ego was conceptualised as organisational-level behaviour through reluctance to collaborate and share information; arrogance, conflict of interest, unfair competition, distrust, organisational conflict, non-compliance, and abuse of authority (Wulandari & Iriani, 2021), measured using 29 negatively worded items. The dependent variable, organisational performance in implementing data integration innovation, comprised responsiveness, quality, quantity, cooperation, timeliness, efficiency, agility, and accuracy (Sadeghi et al., 2024), measured using 25 positively worded items. The instrument was adapted from previous studies and contextualised to the IODF, and its content validity was reviewed by experts. The hypotheses tested were: H_o, sectoral ego has no significant effect on organisational performance; and H_1, sectoral ego has a significant negative effect on organisational performance.

A five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was employed. Descriptive statistics were used to assess indicator and variable achievement levels. SmartPLS analysis was conducted in two stages. First, the measurement model was evaluated using indicator loadings (>0.70), Composite Reliability (>0.70), Cronbach's alpha (>0.70), Average Variance Extracted (AVE >0.50), and discriminant validity using the Heterotrait–Monotrait Ratio (HTMT <0.90) (Sarstedt et al., 2021). Second, the structural model was assessed using R^2 values, path coefficients (β), and bootstrapping procedures to test the significance of relationships between variables (Sonu & Jha, 2025).

RESULTS

Sectoral ego indicator performance

The descriptive statistical analysis results showed the levels of sectoral ego and innovation implementation performance within the Indonesia One Data Forum (IODF). Detail across each indicator, as presented in the following in Table 1.

Descriptive findings of sectoral ego indicators

Based on the negatively worded items, the overall achievement level of sectoral ego indicators remained relatively low (27.55%),

Table 1. Descriptive quantitative of Variables and Indicators

Variable/Indicators	Average Score	Percentage Achievement	Criteria
Sectoral Ego (X)	**1.17**	**27.55**	**Low**
Arrogance	0.81	16.17	Low
Conflict Of Interest	1.23	30.88	Low
Unfair Competition	1.30	31.68	Low
Distrust	1.08	26.79	Low
Conflict	1.33	30.70	Low
Non-Compliance,	1.01	24.80	Low
Abuse Of Authority	1.37	31.82	Low
Performance (Y)	**3.52**	**64.07**	**Moderate**
Responsive	3.76	75.15	High
Quality	3.34	55.71	Moderate
Quantity	3.65	60.76	Moderate
Cooperation	3.29	63.77	Moderate
Ontime	3.56	67.24	High
Efficiency	3.47	65.37	Moderate
Agility	3.50	58.29	Moderate
Accuracy	3.62	66.25	Moderate

Source: Primary data, 2025

Note: The criteria of achievement is categorized into three levels based on the same interval classification: Low (0-33.33%), Moderate (33.34-66.67%), and High (66.68-100%).

suggesting that sectoral ego was not dominant overall within the IODF. Nevertheless, the findings demonstrate that abuse of authority recorded the highest achievement level among all indicators (31.82%). This tendency was more frequently identified among middle-level officials (39.04%). Whereas the achievement levels among top-level officials (31.57%) remained slightly lower than those of staff members (32.19%). This pattern suggests that operational directives are more commonly transmitted through middle-level officials rather than directly by senior leadership, thereby increasing the potential for organisational intervention and authority misuse within inter-organizational coordination processes.

A similarly important pattern emerged unfair competition, which recorded an achievement level of 31.68%. Respondents perceived that other IODF institutions were perceived to perform less affectively in implementing development data integration innovation (39.37%). However, perceptions that their institutions has integrated more data remains relatively low (26.99%). These findings indicate the existence of sectoral ego characterised by a tendency for organisations to perceive themselves as superior without corresponding organisational performance outcomes. This pattern aligns with the relatively high achievement level of the conflict indicator (30.70%). Within the implementation of innovation diffusion, IODF members perceived that development data integration innovation had the potential to generate inter-organisational conflict. Respondents also reported the existence of conflicts among IODF institutions (33.98%). At the individual level, members acknowledged experiencing personal conflict during the implementation of innovation diffusion processes (30.36%).

The conflict of interest indicator likewise remained comparatively high achievement level (30.88%). IODF members continued to perceive that development data integration innovation was perceived as offering limited direct institutional benefits (37.43%). This finding further reinforces the argument that sectoral ego reflects a tendency to prioritise sectoral interests over collective governance objectives. Limited acceptance of innovation diffusion was further reflected in non-compliance indicator (24.80%). Institutionally, non-compliance remained evident (24.58%), while staff members demonstrated the highest level of individual non-compliance (31.31%).

In contrast, arrogance recorded the lowest achievement level among all sectoral ego indicators (16.17%). At the sectoral level, resistance to implementing data integration innovation remained relatively low (17.25%). Nevertheless, a hierarchical discrepancy emerged in which middle-level officials (16.34%) demonstrated slightly higher levels of arrogance than top-level officials (16.05%). This finding may indicate ambiguity in organisational roles and authority structures within the implementation of collaborative data integration governance.

Descriptive findings of innovation diffusion performance indicators

The performance of the Indonesian One Data Forum (IODF) in implementing development data integration innovation remained moderate (64.07%), indicating that innovation diffusion performance had not yet reached an optimal level. Among all indicators, quality emerged as the weakest indicator (55.71%). The quality of integrated data remained below half of the expected integration criteria (45.74%), particularly regarding data standardisation and metadata availability. Nevertheless, in contrast, quantity indicator demonstrated a comparatively higher score (60.76%), reflected in dataset fulfilment (60.44%), dataset completeness (60.44%), and the amount of integrated data (61.81%). This finding may reflect varying institutional understandings of data quality standards required for integrated development data governance.

A similar pattern was observed in the timeliness indicator, which achieved a moderate score (67.24%). IODF demonstrated relatively high punctuality in submitting data (70.51%) and verifying data (72.00%). However, delays remained evident in completing the overall stages of the data integration process (59.20%). This condition may be associated with the relatively low *agility* score (58.29%). The IODF had not yet demonstrated consistent organisational readiness in implementing innovation diffusion processes, both at the individual (59.76%) and sectoral levels (54.58%). These findings suggest limited organisational capacity for innovation adoption. Implementation practices appeared to remain procedural rather than substantively innovation-oriented. Consequently, the stages required to achieve standardised, metadata-compliant, and interoperable data integration had not been fully achieved.

Despite these limitations, the IODF demonstrated a relatively high level of responsiveness (75.15%). Members responded actively to directives related to data integration processes (75.47%), including staff members (74.75%) and top-level officials (75.23%). However, a collaborative discrepancy emerged within the *cooperation* indicator, which remained at a moderate level overall (63.77%). High cooperation scores were observed only in the intensity of collaboration among members within the same institution (72.43%). In contrast, the intensity of collaboration with

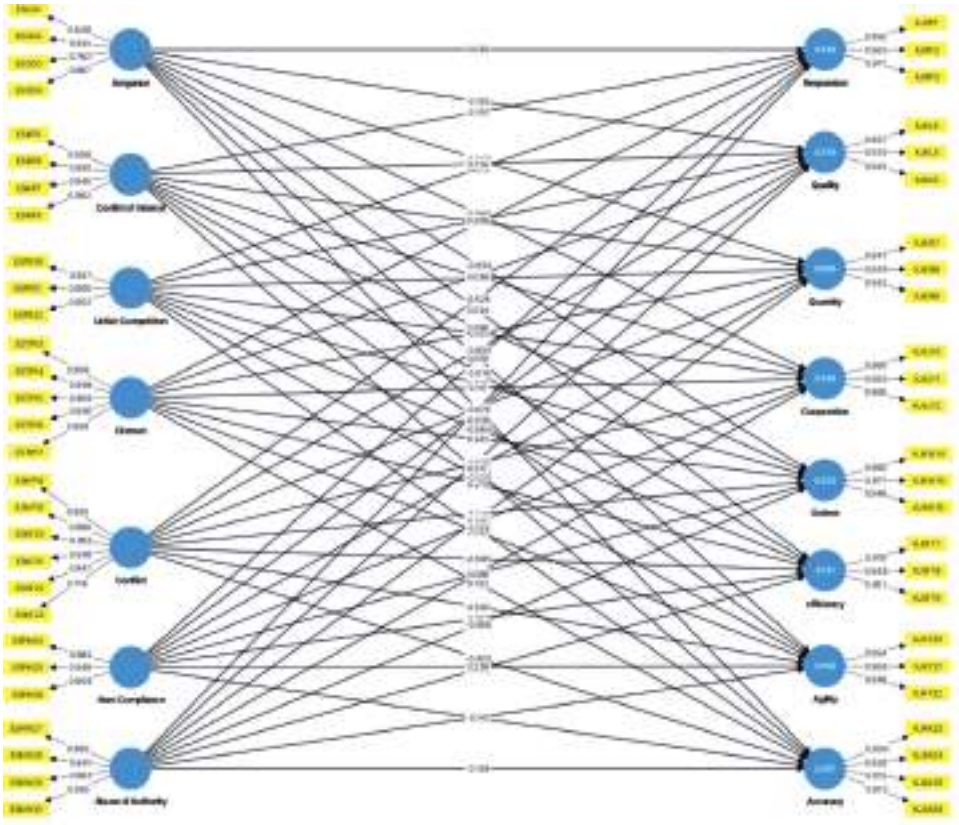


Figure 1. Path coefficient analysis: Sectoral ego to performance in indicators area

IODF members from other institutions remained comparatively low (38.27%). This finding indicates that the IODF continues to face limitations in cross-sector innovation adoption, particularly regarding inter-organisational collaborative capacity. As a result, overall organisational performance has not yet reached a high-performance category because high responsiveness was not accompanied by strong cross-sector collaboration.

Path coefficient analysis results

The influence of sectoral ego on organisational performance and item factor loadings was examined across its indicator dimensions, as illustrated in Figure 1. The SmartPLS measurement model assessment is presented in Table 2. Overall, the results indicate that all constructs satisfied the recommended thresholds for indicator loadings, Composite Reliability, Average Variance Extracted (AVE), and discriminant validity, confirming the adequacy of the measurement model for subsequent path coefficient analysis.

The path coefficient analysis revealed that the influence of sectoral ego on innovation diffusion performance within the Indonesian One Data Forum (IODF) was not uniformly negative across all indicators. Although the initial hypothesis proposed that sectoral ego negatively affects organisational performance, the findings demonstrate more complex and paradoxical relationships among the dimensions of sectoral ego and innovation diffusion performance.

Among the sectoral ego indicators, conflict demonstrated the strongest negative influence across almost all dimensions of organisational performance. Conflict negatively affected quality (β = -0.835), efficiency (β = -0.595), cooperation (β = -0.575), agility (β = -0.593), responsiveness (β = -0.526), quantity (β = -0.532), and timeliness (β = -0.542). These findings indicate that inter-organisational conflict substantially weakens collaborative performance and disrupts the implementation of integrated data innovation within cross-sector governance systems. Similarly, abuse of authority demonstrated consistently negative effects on organisational performance, particularly on quantity (β = -0.355), quality (β = -0.179), agility (β = -0.141), and efficiency (β = -

Table 2. Measurement model assessment results

Variables	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Abuse of Authority	0.969	1.055	0.976	0.910
Accuracy	0.941	0.961	0.957	0.848
Agility	0.954	0.966	0.970	0.916
Arogance	0.902	0.754	0.888	0.668
Conflct of interest	0.940	1.157	0.953	0.837
Conflict	0.953	0.952	0.956	0.786
Cooperation	0.961	0.963	0.975	0.928
Distrust	0.960	1.044	0.967	0.854
Non-Compliance	0.969	1.633	0.975	0.928
Ontime	0.957	0.984	0.972	0.920
Quality	0.913	0.921	0.945	0.852
Quantity	0.942	0.945	0.962	0.895
Responsive	0.939	0.956	0.961	0.891
Unfair Competition	0.891	1.018	0.926	0.808
Efficiency	0.934	0.959	0.958	0.883

Source: Primary analysis results, 2025

Note: Discriminant validity (HTMT) analysis results <0.90 (Supplementary)

0.135). This suggests that hierarchical intervention and authority misuse may hinder innovation diffusion processes and reduce institutional adaptability in collaborative governance practices.

However, several dimensions of sectoral ego demonstrated positive relationships with organisational performance. The most substantial positive effect was identified in the relationship between non-compliance and quality (β = 0.749), followed by quantity (β = 0.517), cooperation (β = 0.416), accuracy (β = 0.396), and responsiveness (β = 0.323). These findings suggest that certain forms of procedural non-compliance may facilitate flexibility and adaptive coordination during the implementation of innovation diffusion processes. A similar pattern was identified in the distrust indicator, which positively influenced agility (β = 0.332), efficiency (β = 0.270), timeliness (β = 0.247), and cooperation (β = 0.111). These findings indicate that distrust does not always function as a purely destructive organisational condition, but may encourage stronger monitoring, faster coordination, and more cautious communication practices among institutions.

In contrast, arrogance demonstrated relatively weak and inconsistent effects across organisational performance dimensions, with most path coefficients remaining close to zero. This finding indicates that sectoral ego within the IODF is influenced more strongly by structural coordination barriers and institutional dynamics than by individual superiority attitudes. The explanatory power of the model remained relatively weak to moderate. The highest R-square value was observed for quality (R^2 = 0.178), followed by responsiveness (R^2 = 0.134), cooperation (R^2 = 0.128), and efficiency (R^2 = 0.111). These results indicate that sectoral ego explains a modest proportion of the variance in organisational performance dimensions. Nevertheless, all path relationships were statistically significant ($p < 0.001$), suggesting that sectoral ego constitutes a relevant, although not exclusive, factor influencing innovation diffusion performance. The relatively low R^2 values further indicate that additional organisational, institutional, and contextual factors may also contribute to performance outcomes.

DISCUSSION

The findings demonstrate that sectoral ego functions as an extension communication barrier in innovation diffusion processes rather than merely as an individual behavioural problem. Among all indicators, conflict emerged as the most destructive dimension, negatively affecting quality, efficiency, cooperation, timeliness, and agility. These findings support previous studies showing that institutional conflict weakens communication, disrupts knowledge exchange, and reduces collective commitment, thereby hindering innovation adoption (Zorlu & Korkmaz, 2021). From an extension communication perspective, communication facilitates collective learning and innovation adoption (Wisataone et al., 2026). Organisations should continue to assess and address the gaps in the less e-ready areas, such as organizational support, to ensure a holistic and sustainable approach, however, achieving and maintaining this level of readiness requires ongoing commitment and strategic planning (Sondarva et al., 2023).

Within the IODF, conflict reflects communication fragmentation that undermines alignment and collaboration in integrated data governance. When communication is dominated by sectoral competition and institutional disagreement, organisations prioritise institutional interests over collective innovation adoption. A similar pattern was observed in the abuse of authority indicator, which negatively influenced quality, quantity, efficiency, and agility. This finding is consistent with evidence that hierarchical domination weakens participatory coordination, adaptive responses, and collaborative innovation (Sharifi et al., 2025; Wen et al., 2025). This study positions sectoral ego as an extension communication barrier within inter-organisational innovation diffusion. The findings indicate that barriers to integrated data governance arise not only from technical limitations but also from fragmented communication structures that restrict information exchange, weaken coordination, and impede innovation diffusion.

One of the most significant findings of this study is the paradoxical relationship between non-compliance and innovation diffusion performance. Contrary to conventional collaborative governance and organisational control perspectives, non-compliance positively influenced quality, quantity, cooperation, responsiveness, and accuracy. Contrary to previous studies linking non-compliance to coordination failure and reduced governance effectiveness (Thimm, 2022), limited procedural deviation may function adaptively within rigid bureaucratic systems.

his finding aligns with innovation diffusion and extension communication perspectives suggesting that innovation adoption often requires flexibility, informal coordination, and adaptive learning under administrative complexity (Li et al., 2024). Consequently, actors may develop informal communication patterns and procedural flexibility to support coordination and data integration.

These findings suggest that innovation diffusion depends not only on communication effectiveness but also on actors' capacity to learn and adapt. Innovation adoption requires behavioural flexibility beyond rigid routines and formal regulation (Martitah et al., 2021; Sharma et al., 2021). Thus, adaptive non-compliance reflects an organisational learning process through which institutions adjust to collaborative innovation demands that have not yet been fully institutionalised. Accordingly, this study shows how adaptive learning can facilitate innovation adoption under bureaucratic constraints.

A further paradoxical finding concerns the positive influence of distrust on agility, efficiency, timeliness, and cooperation within innovation diffusion performance. While collaborative governance studies generally associate distrust with weakened collaboration and coordination (Sever & Bana, 2026), the present findings suggest that distrust may encourage intensive coordination and verification across institutions.

Organisational communication literature suggests that distrust does not eliminate interaction; instead, uncertainty often increases monitoring, verification, and procedural checking to minimise risk (Wahl et al., 2025). Comparable patterns have been reported in inter-agency governance studies, where limited trust stimulated tighter supervision and more active communication among organisations involved in policy implementation (Abdullayev et al., 2025). Perceived institutional unreliability may encourage stronger monitoring and continuous coordination during data integration. These dynamics suggest that collaborative innovation may continue

despite limited trust because coordination remains operationally necessary. Such conditions produce defensive coordination, where interaction is maintained primarily to secure procedural certainty and protect organisational interests (Mittal & Randhawa, 2021).

These findings highlight the limitations of coordination mechanisms based primarily on verification and institutional control, as intensive communication alone does not guarantee collaborative transformation. Extension and social learning perspectives emphasise that sustainable collaboration requires shared understanding, mutual trust, and the internalisation of collective goals among actors. In the IODF context, distrust may strengthen short-term coordination efficiency but also reveals limited collaborative readiness and weak trust-based relationships. These findings highlight the importance of trust-building for sustained collaboration.

The findings indicate that the primary challenges within the IODF are not merely technical or administrative, but also behavioural and communicative in nature. Although responsiveness remained high, cross-sector cooperation remained comparatively weak, indicating that institutional actors tended to comply with formal directives without fully developing collaborative commitment across organisational boundaries. This finding supports previous organisational communication studies suggesting that formal communication mechanisms are effective for coordination and information exchange, yet often insufficient for fostering substantive collaborative transformation within complex governance systems (Maurer et al., 2023). Similar patterns have been identified in public sector innovation research, where procedural compliance does not necessarily produce collective ownership or inter-organisational collaboration (Calò et al., 2024).

From an extension communication perspective, these findings reflect incomplete innovation adoption within bureaucratic systems. Extension and social learning theories emphasise that innovation diffusion requires behavioural change, participatory engagement, and the internalisation of shared goals among actors (Feder & Savastano, 2006; Putra & Pedersen, 2018). The findings suggest that extension communication complements organisational communication by explaining how behavioural change and collective commitment influence innovation diffusion performance within collaborative governance systems.

CONCLUSION

The study demonstrates that sectoral ego influences data integration innovation performance in both constraining and adaptive ways within collaborative governance systems. Conflict and abuse of authority undermine performance by restricting communication, coordination, and cross-sector collaboration, whereas non-compliance and distrust may generate adaptive responses that sustain organisational effectiveness under bureaucratic constraints. These findings indicate that innovation diffusion in integrated data governance depends not only on technological readiness and regulatory arrangements but also on the capacity of institutions to exchange knowledge, build collaborative commitment, and adapt to new practices. The study contributes to extension communication scholarship by showing that barriers to innovation diffusion arise not only from technical and organisational factors but also from communication structures that shape learning, trust-building, and behavioural change across organisations. Strengthening extension communication processes may therefore enhance collaborative readiness and support more sustainable data integration initiatives.

DECLARATIONS

Ethics approval and informed consent: Informed consent was obtained from the Ethics Committee of Universitas Gadjah Mada approval number (NO: KE/UGM/195/EC/2025). All participants provided informed consent prior to participation. Consent for publication not applicable as no identifiable personal data were included in this study.

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Research Article

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Gender Differences in Production Efficiency and Food Security among Rice Farmers in Ebonyi State

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HIGHLIGHTS

- Female swamp rice farmers recorded the highest technology gap ratio, despite. persistent technological inadequacies in rice production systems.
- Food insecurity was most severe among male swamp rice farmers, with a high proportion classified as food-insecure households.
- Allocative inefficiency contributed more to low economic performance than technical inefficiency among upland and swamp rice farmers.

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Keywords: Agricultural extension, Food security, Gender analysis, Production efficiency, Rice farmers, Technology adoption.

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ABSTRACT

The study examined gender, production efficiency, and food security among smallholder upland and swamp rice farmers in Ebonyi State, Nigeria, between January and December 2025. The study determined technical, allocative, and economic efficiencies by gender, assessed food security status, and identified technology gaps and inadequacies. A multi-stage sampling procedure selected 180 farmers comprising 72 upland and 108 swamp rice farmers. Data were analyzed using Data Envelopment Analysis, Foster-Greer-Thorbecke index, Technology Gap Ratio, and Technology Inadequacy Ratio. The results showed low technical and economic efficiencies across production systems. Mean technical efficiency under constant returns to scale was 0.337 for upland farmers, 0.616 for male swamp farmers, and 0.532 for female swamp farmers. Economic efficiency was highest among female upland farmers (0.307) and lowest among female swamp farmers (0.133). Food insecurity was most severe among male swamp farmers, with headcount ratio, depth, and severity indices of 0.852, 0.382, and 0.180, respectively. Female swamp farmers recorded the highest technology gap ratio (91.09%). The study concluded that gender disparities and technology inadequacies significantly influenced production efficiency and food security among rice farmers in Ebonyi State.

INTRODUCTION

Rice remains one of the major staple foods in Nigeria and contributes significantly to food security, employment generation, and rural livelihoods. Nigeria cultivates rice across several agro-ecological systems, particularly upland and swamp ecosystems commonly practiced in Ebonyi State, one of the leading rice-producing states in the country (FAO, 2023; Chima et al., 2024).

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Despite favourable agro-ecological conditions for rice cultivation, productivity among smallholder rice farmers remains relatively low, estimated at about 2–3 tons per hectare across major production systems, largely due to continued reliance on traditional farming practices and low-input technologies (Kamai et al., 2020). In contrast, global average rice yields are reported at approximately 4.7 tons per hectare, with high-performing production systems exceeding 6 tons per hectare (FAO, 2024). This difference highlights a persistent and substantial yield gap between smallholder rice farmers and global productivity benchmarks.

Improving production efficiency among rice farmers remains critical because inefficient utilization of productive resources limits output and farm profitability. Smallholder farmers in Ebonyi State often experience inadequate access to improved seeds, fertilizers, mechanization, credit facilities, and extension services, thereby reducing their capacity to optimize production resources (Ezeh et al., 2022). Weak extension support and poor dissemination of improved rice technologies further constrain technology adoption and resource-use efficiency among rural farming households (Silva, 2023; Chandra et al., 2023).

Food security among rice farming households is strongly influenced by gender roles and access to productive resources. Male and female farmers differ in labour participation, access to extension information, credit facilities, land ownership, and innovation platforms, thereby affecting production efficiency and household welfare outcomes (Ezeaputa et al., 2020). Women are more actively involved in planting, processing, and marketing activities, while men dominate land preparation and harvesting operations. Gender disparities in access to agricultural information and extension services continue to influence technology adoption and productivity among smallholder farmers (Silva, 2023).

Agricultural extension services play an important role in improving farmers' technical knowledge, strengthening innovation dissemination, and promoting climate-smart agricultural practices. Effective extension delivery systems enhance farmers' ability to adopt improved production technologies and efficiently utilize available production resources. Recent studies emphasize that extension interactions, ICT utilization, and farmer information networks significantly improve agricultural technology adoption and farm productivity (Nain et al., 2015; Gogoi et al., 2022; Niranjan et al., 2023; Chandra et al., 2023). Strengthening gender-responsive extension systems may therefore improve production efficiency and food security among rice farmers.

Although previous studies examine production efficiency, food security, and gender issues separately, limited empirical evidence exists on how gender disparities, extension-related factors, technology gaps, and production systems jointly influence production efficiency and food security among upland and swamp rice farmers in Ebonyi State (Aryal et al., 2019; Munonye et al., 2023). This study therefore examines the technical, allocative, and economic efficiencies of upland and swamp rice farmers by gender, assesses the food security status of rice farming households, and identifies technology gaps among rice farmers in Ebonyi State, Nigeria.

METHODOLOGY

This study was conducted in Ebonyi State, Nigeria, one of the major rice-producing states in southeastern Nigeria. The state was divided into three agricultural zones: Ebonyi North, Ebonyi Central, and Ebonyi South. Ebonyi State had an estimated population of about 2.9 million people in 2016 (National Population Commission [NPC], 2016) and occupied a land area of approximately 5,935 km² (Nwahia et al., 2020). Agriculture constituted the major occupation of the residents, with most rural households engaged in crop production activities. The state experienced a humid tropical climate characterized by high rainfall and favourable environmental conditions suitable for rice cultivation (Onyeneke, 2021). Major food crops cultivated in the area included rice, cassava, yams, and vegetables. Rice production in Ebonyi State was practiced under upland and swamp production systems. Upland rice farming was concentrated mainly in Izzi and Ikwo Local Government Areas (LGAs), while swamp rice cultivation was predominant in Ohaozara and other lowland areas (Chidiebere-Mark et al., 2019). The soils in the state were predominantly loamy and clayey, making them suitable for rice production. A multi-stage sampling procedure involving five stages was used for respondent selection. In the first stage, three LGAs namely Izzi, Ikwo, and Ohaozara were purposively selected based on the intensity of rice production. In the second stage, three communities were randomly selected from each LGA, resulting in nine communities. The third stage involved the random selection of two villages from each community, giving a total of eighteen villages. In the fourth stage, rice farmers were stratified into upland and swamp rice farmers and further categorized into male upland, female upland, male swamp, and female swamp farmers. In the fifth stage, proportionate random sampling was used to select respondents from the sampling frame obtained during the pre-survey exercise. A total of 180 rice farmers were selected for the study, comprising 72 upland rice farmers (36 males and 36 females) and 108 swamp rice farmers (54 males and 54 females). Primary data were collected using structured questionnaires and interview schedules. Data collected were cross-sectional in nature and were analysed using descriptive and inferential statistics. The Cobb-Douglas production function was used to estimate technical, allocative, and economic efficiencies among rice farmers. Extension-related variables such as access to extension services, adoption of improved rice technologies, and participation in advisory activities were also considered because of their influence on technology adoption and efficient resource utilization among smallholder farmers. Gender analysis was conducted using descriptive statistics, including frequencies, percentages, and mean comparisons. Variables examined included access to agricultural extension services, improved seed utilization, fertilizer application, agricultural credit, farm size, and technology adoption. These indicators were compared across male and female rice farmers within upland and swamp production systems to identify gender-based disparities in access to productive resources and agricultural support services.

Data Envelopment Analysis (DEA) VRS output-oriented model used by Kohl et al. (2019) and Ismail et al. (2018) was adopted for this study.

Technical efficiency refers to the ability of a DMU to obtain maximum output from a given set of inputs. An input-oriented DEA model was used to assess how much input quantities were proportionally reduced without changing the output quantities. The

choice of DEA in this research study is that it does not assume a specific production function and does not introduce any statistical noise. The model is specified as follows:

Minimize θ
Subject to:
$\Sigma\lambda_j$ X{ij} ≤ θnx{nj}, for all inputs i … Equation (1)
Σλj Y{ij} ≥ Y{nj}, for all outputs i
λj ≥ 0, for all j

Where, Xij is the quantity of inputs (i) used by the j farmers, the inputs are the farm size (Ha), labour (man-hour), capital investment (naira), fertilizer (kg), agrochemicals (litres), rice grain (kg), Y_{ij} = quantity of output (i) produced by j farmers, λj = non-negative weights assigned to each DMU, θ = efficiency score (θ ≤ θ ≤ 1), n = number of DMU

Technical efficiency was computed, and allocative efficiency was derived by comparing the cost-minimizing input combination to the technically efficient input usage. The EE score for a given field n was obtained by first solving the following cost-minimizing LP model:

$MC_n = \min_{\lambda xij} \Sigma^I_{i=1} PnjXnj$ ... Equation (2)
Subject to $\Sigma^I_{i=1}\lambda iXij - Xnj \leq 0$
$\Sigma^I_{i=1}\lambda iYik - Xnk \geq 0$
$\Sigma^I_{i=1}\lambda_I = 1$
$\lambda_i \geq 0$

Where, MC_n = the minimum total cost for field *n; Pnj* = the price for input *j* on the field *n*; and X^*nj = the cost-minimizing the level of input *j* on field n given its input price and output levels. All other variables in equation 2.6 are as defined previously. The constraints $\Sigma^I_{i=1}\lambda_I = 1$ ensures that the minimum total costs for the field are calculated under the VRS assumption. Economic efficiency (EE_n) for each field is then calculated using the following equation:

$$EE_n = \frac{\Sigma^I_{i=1} PnjXnj}{\Sigma^I_{i=1} PnjXnj} \quad \text{... Equation (3)}$$

Where the numerator $\Sigma^I_{i=1} PnjXnj$ = the minimum total cost obtained for field n using equation (3.3) and the denominator $\Sigma^I_{i=1} PnjXnj$ = the actual total cost observed for field n. The EE_n for a given field takes on a value ≤ 1; with an EEn = 1 indicating the field is economically efficient and EEn < 1 indicating the field is economically inefficient. The EE for a DMU can also be represented as the product of both the TE and AE for the DMU or EEn = TEn x AEn (Farrell, 1957).

$$AE = \frac{EE}{TE} \quad \text{… Equation (4)}$$

AE will be ≤ 1, with AE = 1, meaning efficient allocation of resources and AE < 1, meaning allocative inefficient.

To assess the effect of gender on efficiency, the DEA efficiency scores (TE and AE) were regressed against gender, age, farm size, farming experience, household size, and rice production system using a binary logistic regression model. This allowed for a statistical test whether gender significantly affects efficiency levels.

Foster-Greer-Thorbecke (FGT) decomposable indices as used by Amusan et al. (2023). The model is specified as follows;

$$P_a = \frac{1}{n}\sum\left(\frac{Z - Y_i}{Z}\right)^a \text{ x I } (Y_i < Z) \quad \text{... Equation (5)}$$

Where, I (Y_i < Z) = is a food security indicator function that takes the value of 1(food secured) if Yi > Z, and 0 (food insecure) if Yi < Z, Z = Minimum calorie requirements per day per adult equivalent (kcal), Y_i = Average monthly expenditure of the individual farmers (₦), α = is a non-negative parameter that takes the value of zero (0) for the headcount ratio, 1 for the food insecurity gap index, and 2 for the squared food insecurity gap index, n = Total sample size

The headcount ratio (HCR) is expressed as;

$$HCR = \frac{N}{n} \quad \text{… Equation (6)}$$

Where, N = Number of farmers living below the recommended minimum calorie requirement per day; n = sample size

$$\text{Food Insecurity Gap Index (ij)} = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{Z - C}{Z}\right) \quad \text{... Equation (7)}$$

Where, q_{ij} = Number of food-insecure households (households for food consumption C < Z), Z_{ij} = food secured threshold (2,250 kg/day), C_{ij} = food consumption level (expenditure on food) of the ith food-insecure household, i = i^{th} household by gender, j = j^{th} production system.

The study adopted the model used by Dossou-Yovo et al. (2020) to find out Technology Gap Ratio. The model was expressed as follows:

$$TGR_{ji} = \frac{\text{Actual Rice Yield (kg)}}{\text{Potential Yield (kg)}} \text{ x } 100 \quad \text{… Equation (8)}$$

Where, TGR = Technology Gap Ratio

Actual yield is the quantity of rice (upland and swamp rice) tons/ha that a farmer harvests from their field under current practices and conditions. Potential yield is the maximum possible yield of (upland and swamp rice) tons/ha that can be achieved under optimal conditions no limitations from pests, water, or nutrients, and using the best management practices for a given rice variety and environment.

According to Kamai et al. (2020) potential yield for upland rice is between 4.0 to 6.0 tons/ha under optimal conditions using the best farm management practices, while the potential yield for swamp rice is between 6.2 to 8.0 tons/ha under optimal conditions using the best farm management practices.

If TGR = 50%, it means a moderate gap/partial gap in technology, If TGR < 50%, it means a high gap/wide gap in technology and If TGR > 50%, it implies a low gap/closing the technology gap.

$$\text{Technology Inadequacy Ratio} = 1 - \frac{\text{No. of Technology Adopted}}{\text{Total No. of Technology Considered}} \quad \text{…Equation (9)}$$

The eight essential components of rice production technology were considered. They include improved seeds, use of chemical fertilizers, agrochemical use, machine seed broadcasting, irrigation, machine seed transplanting, use of automated water sprinklers, and access to agricultural extension services. Each respondent received a binary score, where 1 indicated adoption of the technology and 0 indicated non-adoption.

If the TIR = 0, it implies that technology is adequate, the farmers have adopted all the technology, If the TIR > 0, it implies that technology is inadequate, and the farmers have not adopted all the technology.

RESULTS

The results of the level of technical, allocative and economic efficiencies by gender in upland and swamp rice production systems are presented in Tables 1 and 2.

Table 1 presents the technical and scale efficiency estimates of upland and swamp rice farmers by gender. The results showed that male and female upland rice farmers recorded relatively low mean overall technical efficiency scores of 0.337, indicating that they operated substantially below the production frontier and could potentially increase output by approximately 66.3% using existing resources and available technologies. In contrast, male swamp farmers recorded the highest technical efficiency score (0.616), followed by female swamp farmers (0.532), suggesting relatively better resource utilization under swamp production systems. The generally low scale efficiency values across all farmer categories indicate that most farmers were not operating at optimal production scales. This implies that inefficiencies were attributable not only to technical limitations but also to poor scale management and suboptimal allocation of productive resources.

Table 2 presents the allocative and economic efficiency estimates of rice farmers across gender and production systems. Female upland farmers recorded the highest allocative efficiency score (0.519), while female swamp farmers recorded the lowest (0.386). Similarly, economic efficiency was highest among female upland farmers (0.285) and lowest among male swamp farmers (0.166). These findings indicate that farmers were unable to combine production inputs in cost-minimizing proportions, resulting in substantial economic inefficiencies.

Table 3 presents the food security status of rice farmers across gender and production systems. Food insecurity was most severe among male swamp farmers, with a headcount ratio of 0.852, indicating that 85.2% of households in this category were food insecure. Female swamp farmers also recorded a relatively high incidence of food insecurity (68.5%). In contrast, male and female upland farmers recorded lower food insecurity incidences of 47.2% and 55.6%, respectively. The depth and severity indices further revealed that food insecurity among swamp farmers was not only more widespread but also more intense.

Table 4 presents the technology gap ratio among rice farmers by gender and production system. Female swamp farmers recorded the highest technology gap ratio (91.09%), followed by female upland farmers (78.47%). Male upland and male swamp farmers recorded lower technology gap ratios of 47.40% and 48.96%, respectively. These findings indicate substantial differences in the utilization of available rice production technologies.

Table 5 presents the technology inadequacy ratio among rice farmers. Male and female upland farmers recorded technology inadequacy ratios of 0.44, while male and female swamp farmers recorded lower ratios of 0.22. The pooled technology inadequacy ratio was 0.33. These findings indicate that none of the farmer groups adopted all recommended rice production technologies and that important gaps remained between recommended and actual farming practices.

Table 6 presents the distribution of farmers across technology gap categories. The majority of farmers belonged to the technology gap-closing category, including 61.1% of male upland farmers, 66.7% of female upland farmers, and 63.0% of female swamp farmers. However, only 42.6% of male swamp farmers belonged to this

Table 1. Technical and scale efficiencies of upland and swamp rice farmers by gender

Indices	Male Upland			Female Upland		
	OTE (%)	PTE (%)	SE (%)	OTE (%)	PTE (%)	SE (%)
0.05 – 0.35	66.7	69.4	72.2	72.2	75.0	66.7
0.35 – 0.66	19.4	13.9	11.1	13.9	13.9	19.4
0.65 – 0.95	5.6	11.1	5.6	5.6	8.3	11.1
0.95 – 1.25	8.2	5.6	11.1	8.3	2.8	2.8
Total	100	100	100	100	100	100
Mean	0.337	0.887	0.385	0.337	0.524	0.777
Max	1.000	1.000	1.000	1.000	1.000	1.000
Min	0.051	0.288	0.051	0.035	0.041	0.074
Indices	Male Swamp			Female Swamp		
	OTE (%)	PTE (%)	SE (%)	OTE (%)	PTE (%)	SE (%)
0.18 – 0.58	46.3	46.3	44.4	44.4	42.6	48.1
0.58 – 0.98	37.0	35.2	37.0	31.5	29.6	27.8
0.98 – 1.38	16.7	18.5	18.6	24.1	27.8	24.1
Total	100	100	100	100	100	100
Mean	0.616	0.889	0.710	0.532	0.851	0.658
Max	1.000	1.000	1.000	1.000	1.000	1.000
Min	0.188	0.220	0.231	0.136	0.162	0.159

Source: Computed from Field Survey Data, 2025 MaxDEA Software Overall Technical Efficiency (OTE), Pure Technical Efficiency (PTE), Scale Efficiency (SE)

Table 2. Allocative and Economic Efficiencies of Rice Farmers by Gender

Indices	Male Upland			Female Upland		
	OAE (%)	PAE (%)	EE (%)	OAE (%)	PAE (%)	EE (%)
0.05 – 0.35	47.2	52.7	75.0	66.7	47.2	25.0
0.35 – 0.66	33.3	22.2	19.4	8.3	44.4	58.3
0.65 – 0.95	16.7	22.2	2.8	19.4	5.6	13.9
0.95 – 1.25	2.8	2.9	2.8	5.6	2.8	2.8
Total	100	100	100	100	100	100
Mean	0.507	0.177	0.285	0.519	0.198	0.307
Max	1.000	1.000	1.000	1.000	1.000	1.000
Min	0.289	0.244	0.089	0.049	0.001	0.002
Indices	Male Swamp			Female Swamp		
	OAE (%)	PAE (%)	EE (%)	OAE (%)	PAE (%)	EE (%)
0.18 – 0.58	46.3	46.3	85.2	61.1	61.1	88.9
0.58 – 0.98	50.0	48.1	11.1	33.3	31.5	5.6
0.98 – 1.38	3.7	5.6	3.7	5.6	7.4	5.6
Total	100	100	100	100	100	100
Mean	0.470	0.264	0.166	0.386	0.205	0.133
Max	1.000	1.000	1.000	0.999	0.999	0.999
Min	0.056	0.003	0.001	0.031	0.001	0.003

Source: Computed from Field Survey Data, 2025 MaxDEA Software Overall Allocative Efficiency (OAE), Pure Allocative Efficiency (PAE), Economic Efficiency (EE)

Table 3. Food Security Status of Rice Farmers by Gender

Groups	n	Food Insecure	Headcount Ratio	Extent of Insecurity	Severity of Insecurity
Male Upland	36	17	0.472	0.186	0.010
Female Upland	36	20	0.556	0.192	0.050
Male Swamp	54	46	0.852	0.382	0.180
Female Swamp	54	37	0.685	0.257	0.120
Pooled Sample	180	120	0.667	0.102	0.204

Table 4. Technology Gap Ratio among Rice Farmers

Group	Actual Yield (kg)	Potential Yield (kg)	TGR (%)	Remark
Male Upland	1263.89	2666.67	47.40	Wide gap
Female Upland	2004.17	2554.17	78.47	Closing gap
Male Swamp	781.48	1596.0	48.96	Wide gap
Female Swamp	1636.11	1796.20	91.09	Closing gap

TGR = 50% (Moderate gap), TGR > 50% (Closing gap), TGR < 50% (Wide gap)

Table 5. Technology Inadequacy among Rice Farmers by Gender

Group	NTA	TNTC	$\text{TIR} = (1 - \frac{NTA}{TNTC})$	Remark
Male Upland	5	9	0.44	Technology Inadequacy
Female Upland	5	9	0.44	Technology Inadequacy
Male Swamp	7	9	0.22	Technology Inadequacy
Female Swamp	7	9	0.22	Technology Inadequacy
Pooled Sample	24	36	0.33	Technology Inadequacy

NTA (Number of technologies adopted), TNTC (Total number of technologies considered), TIR (Technology Inadequacy Ratio)

category. Conversely, 55.5% of male swamp farmers fell within the wide-gap category. Table 7 presents the Pearson correlation analysis between technology gap ratio and technology inadequacy ratio across gender and production systems. The results revealed positive but statistically insignificant relationships among male upland farmers ($r = 0.097$; $p = 0.574$), female upland farmers ($r = 0.215$; $p = 0.207$), male swamp farmers ($r = 0.060$; $p = 0.667$), and female swamp farmers ($r = 0.196$; $p = 0.156$).

Tale 6. Technology Gap Categories among Rice Farmers by Gender in percent

Technology Gap	Male Upland	Female Upland	Male Swamp	Female Swamp
Closing Gap	61.1	66.7	42.6	63.0
Moderate Gap	2.8	5.6	1.9	1.9
Wide Gap	36.1	27.7	55.5	35.1
Total	100	100	100	100

Table 7. Pearson correlation between technology gap and technology inadequacy rations across gender and rice production systems

Group	Variables compared	Pearson's R	P – value	Interpretation	Decision @ 5%
Male Upland	TGR vs TIR	0.097	0.574	Not significant	Accepted
Female Upland	TGR vs TIR	0.215	0.207	Not significant	Accepted
Male Swamp	TGR vs TIR	0.060	0.667	Not significant	Accepted
Female Swamp	TGR vs TIR	0.196	0.156	Not significant	Accepted

TGR = Technology Gap Ratio, TIR = Technology Inadequacy Ratio.

DISCUSSION

The low efficiency levels observed among upland farmers may be linked to the inherent production challenges associated with upland rice cultivation. Upland systems depend largely on rainfall and are more susceptible to moisture stress, declining soil fertility, weed infestation, and climatic variability. These constraints reduce farmers' ability to achieve maximum output from available resources. In addition, many upland farmers rely on traditional production methods, low-input technologies, and family labour, which may limit productivity. Fragmented landholdings further constrain mechanization and efficient resource coordination, thereby reducing scale efficiency.

The relatively higher efficiency observed among swamp farmers highlights the importance of ecological suitability in rice production. Swamp ecosystems generally provide favourable water conditions and improved soil moisture, thereby supporting higher productivity. These findings agree with Gogoi et al. (2022), who reported that farmer exposure to improved production practices, extension contact, and technical knowledge significantly enhanced rice productivity and technology utilization.

Despite the higher technical efficiency of swamp farmers, persistent scale inefficiencies suggest that many farmers still fail to combine production resources optimally. Such inefficiencies may arise from limited access to land, labour shortages, inadequate financial resources, and weak managerial capacity. Ehirim et al. (2022) similarly reported that efficiency losses were strongly influenced by variations in farm size and operational scale. The findings therefore suggest that improving managerial capacity and resource coordination could substantially enhance rice productivity.

The efficiency differentials observed between male and female farmers further indicate that gender-related factors continue to influence production outcomes. Although women demonstrated comparable and, in some cases, better resource coordination, they often face greater barriers in accessing land, credit, mechanization services, improved seeds, and extension support. These constraints may limit their ability to achieve higher efficiency levels despite their active participation in rice production. The findings therefore reinforce evidence that gender disparities remain important determinants of agricultural productivity among smallholder farmers in sub-Saharan Africa.

The low allocative efficiency scores suggest that farmers faced difficulties in making optimal resource allocation decisions. Such inefficiencies may result from inadequate market information, fluctuations in input prices, limited managerial skills, and poor access to credit. Many smallholder farmers lack the financial capacity required to purchase productive inputs in economically optimal quantities. Consequently, they often rely on suboptimal input combinations that reduce profitability.

The results further show that relatively higher technical efficiency does not necessarily translate into economic efficiency. Although swamp farmers performed better technically, they recorded comparatively lower economic efficiency levels. This may be due to the higher production costs associated with swamp rice cultivation, including labour-intensive operations, water management requirements, and vulnerability to flooding. Consequently, increased output does not always correspond to higher profitability.

The findings corroborate Michael et al. (2021), who reported that inefficient allocation of production resources significantly reduced farm profitability among smallholder farmers. Similarly, Chandra et al. (2023) found that farmers' access to information and production resources played an important role in determining production outcomes. The present results therefore emphasize the need to strengthen farmers' managerial capacity, improve access to market information, and enhance agricultural financing opportunities. Such interventions would improve allocative efficiency and enable farmers to convert technical gains into improved economic performance.

These findings demonstrate that higher technical efficiency alone does not guarantee improved household food security. Although swamp farmers generally recorded better production efficiency, they remained highly vulnerable to food insecurity. This suggests that food security is influenced by several factors beyond agricultural productivity, including income stability, market access, household expenditure patterns, and exposure to production risks.

The higher food insecurity observed among swamp farmers may be associated with environmental uncertainties such as flooding, unstable yields, and crop losses. Frequent flooding can reduce

harvest volumes, increase post-harvest losses, and disrupt household income streams. Such conditions may weaken household purchasing power and limit access to adequate food throughout the year. Consequently, households may remain food insecure despite participating actively in rice production.

The findings are consistent with Munonye et al. (2023) and Esheya et al. (2024), who reported widespread food insecurity among farming households in Ebonyi State. Similar studies have shown that participation in agriculture does not automatically guarantee food security because household welfare depends on broader socioeconomic conditions. The present results therefore suggest that policies aimed at improving productivity should be complemented by interventions that strengthen household resilience, diversify income sources, and improve market access.

Gender disparities also appeared to influence food security outcomes. Women often experience limited access to productive resources and income-generating opportunities, thereby increasing household vulnerability. Njoku et al. (2025) similarly reported that inequalities in access to agricultural resources significantly influenced household welfare and food security outcomes. The findings therefore underscore the importance of gender-sensitive agricultural interventions. Furthermore, limited access to extension information and climate-smart advisory services may reduce farmers' capacity to manage production risks effectively. Silva (2023) observed that stronger information networks and social learning systems improved farmers' adaptive capacity and technology adoption. Strengthening extension communication systems may therefore contribute significantly to improved food security among rice farming households.

The results suggest that female farmers were relatively more successful in translating available technologies into productive outcomes despite facing resource constraints. However, the persistence of technology gaps across all groups indicates that improved rice technologies remained underutilized. This suggests that awareness alone is insufficient to guarantee effective adoption and utilization.

Several factors may explain the observed technology gaps, including limited access to credit, inadequate technical knowledge, high input costs, and poor access to improved production inputs. Farmers who lack financial resources may be unable to adopt improved seeds, fertilizers, herbicides, and mechanized technologies required for modern rice production. Ibrahim et al. (2024) similarly reported that inadequate extension support and limited access to productive resources constrained technology adoption among rice farmers. The findings therefore suggest that improving technology utilization requires both enhanced awareness and improved access to productive resources.

The persistence of technology inadequacies suggests weaknesses in agricultural extension and innovation dissemination systems. Many farmers continue to rely on traditional production methods despite increasing awareness of improved technologies. Weak extension-farmer interaction, inadequate technical training, and limited practical demonstrations may have constrained effective adoption.

In many rural communities, extension services are challenged by inadequate staffing, poor funding, and logistical limitations. Consequently, farmers often receive insufficient technical guidance. Gogoi et al. (2022) reported that regular contact with extension agents significantly influenced rice technology adoption, while Chandra et al. (2023) found that ICT-based information platforms improved farmers' decision-making and technology utilization.

The findings have important implications for agricultural extension education. Persistent inefficiencies, food insecurity, and technology inadequacies indicate the need for stronger extension systems capable of promoting innovation dissemination, farmer learning, and climate-smart agricultural practices. Particular attention should be given to gender-responsive extension approaches that address the specific constraints faced by female farmers.

The predominance of farmers in the technology gap-closing category suggests that substantial progress has been made in narrowing technology gaps among rice farmers. This may reflect increasing awareness of improved production technologies and the positive effects of extension activities. However, the large proportion of farmers in the wide-gap category indicates that technology adoption remains uneven.

The particularly high proportion of male swamp farmers within the wide-gap category suggests the presence of significant barriers to technology utilization. These barriers may include financial constraints, inadequate technical knowledge, poor access to inputs, and environmental challenges associated with swamp rice production. The finding is consistent with the technology gap ratio results, which showed considerable variation in technology utilization across farmer groups.

The low proportion of farmers in the moderate-gap category suggests that farmers tended to cluster at either end of the adoption spectrum. Consequently, interventions should focus on farmers within the wide-gap category, where the greatest opportunities for productivity improvement exist. Strengthening farmer training, demonstration programmes, cooperative learning platforms, and ICT-enabled advisory services could accelerate movement from the wide-gap category to the technology gap-closing category.

The positive coefficients suggest that technology inadequacy tended to increase alongside technology gaps. However, the lack of statistical significance indicates that technology inadequacy alone did not explain variations in technology gaps among the farmer groups. This implies that additional factors such as managerial ability, access to extension services, environmental conditions, input quality, and financial resources may have influenced technology utilization outcomes.

The findings suggest that reducing technology gaps requires more than promoting technology adoption alone. Integrated interventions that combine technology dissemination with improved access to credit, extension support, productive inputs, and farmer training are likely to generate greater improvements in productivity, efficiency, and household welfare among rice farmers in Ebonyi State.

CONCLUSION

The study concluded that production efficiency, food security, and technology utilization differed across gender groups and rice production systems in Ebonyi State. Although swamp farmers generally recorded higher technical efficiency, food insecurity

remained more pronounced among them due to ecological risks and unstable production conditions. Persistent inefficiencies in resource allocation, scale management, and technology use limited productivity and profitability among rice farmers. Gender disparities in access to land, credit, extension services, and improved technologies further influenced production outcomes and household welfare. The findings also revealed that technology inadequacies and gaps persisted because of weak extension support and limited dissemination of improved rice technologies. Therefore, improving rice productivity and food security requires gender-responsive extension services, enhanced access to credit and productive resources, farmer capacity building, and wider adoption of climate-smart technologies. Strengthening participatory and ICT-enabled advisory systems could significantly improve technology uptake, efficiency, and rural livelihoods.

DECLARATIONS

Ethics approval and informed consent: This research was conducted in accordance with established ethical standards for social science research. Verbal informed consent was obtained from all participating rice farmers before data collection. Respondents were assured of confidentiality, anonymity, and the voluntary nature of their participation throughout the study.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors further declare that they have thoroughly reviewed, revised, and edited the manuscript and take full responsibility for the final content of this publication. The authors declare that there is no conflict of interest regarding the publication of this paper.

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Adoption and Determinants of Sustainable Agricultural Practices (SAPs) among Pineapple Growers in Nagaland

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HIGHLIGHTS

- Post-harvest management showed highest adoption across the three districts.
- Significant inter-district differences in SAP adoption were observed.
- "Land use and Income" factor accounted as the major determinant of SAP adoption.

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ABSTRACT

The study assessed the extent and determinants of adoption of sustainable agricultural practices (SAPs) among pineapple growers in Dimapur, Peren and Mokokchung districts of Nagaland during 2022-2023. A total of 275 respondents were selected using proportionate random sampling. Adoption was assessed using an adoption index covering agronomic practices, resource management, pest and disease management and post-harvest management. Inter-district differences were analysed using z-test and determinants were identified through factor analysis. Results revealed that majority (64.73%) of the respondents had medium level of adoption. Post-harvest management recorded the highest adoption, whereas resource management practices showed comparatively lower adoption. Significant differences in adoption indices were observed among the districts ($p<0.01$), with Mokokchung recording the highest mean adoption index (57.56). Factor analysis extracted eight components explaining 62.49 per cent of the total variance, with "land use and income" emerging as the major determinant, followed by motivational factors and extension access. The study highlights the need for location-specific extension strategies, strengthened institutional support and capacity building interventions to enhance sustainable pineapple cultivation in Nagaland.

INTRODUCTION

Pineapple (*Ananas comosus*) is an economically important horticultural crop in Nagaland. The state's diverse and favourable agro-climatic conditions enable its cultivation across all the districts. According to the Directorate of Economics and Statistics (2025), pineapple was cultivated in an area of 9,053.12 hectares with a total production of 1,23,285.78 metric tons in Nagaland during 2023-24, with Dimapur leading in production (38,004 metric tons). Pineapple cultivation in the state is largely based on traditional and low input production systems, providing scope for sustainable agricultural practices (SAPs) to enhance productivity and sustainability of resources.

Sustainable agricultural practices such as improved agronomic management, integrated nutrient management, integrated pest management and post-harvest handling play a crucial role in maintaining soil health, reducing environmental risks and improving farm profitability. However, the adoption of such practices varies depending on farmers' socio-economic characteristics, psychological attributes and access to institutional support (Priya & Singh, 2022;

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Kumar et al., 2023; Bhujel & Joshi, 2024). Previous studies have reported that factors such as landholding size, income, education, extension contact and training exposure significantly influence adoption behaviour (Meena et al., 2023; Thangjam et al., 2024).

Although pineapple is widely cultivated in Nagaland, it is evident that the extent of adoption of sustainable practices and the determinants influencing adoption among pineapple growers remains limited. Understanding these aspects is essential for facilitating effective research, extension and policy interventions. Therefore, the present study was undertaken to assess the extent of adoption of sustainable agricultural practices among pineapple growers and identify the determinants influencing adoption of sustainable pineapple cultivation practices.

METHODOLOGY

The study was conducted in three major pineapple growing districts of Nagaland; Dimapur, Peren and Mokokchung, purposively selected based on their area and production under pineapple with data collection during 2022-23. Four Rural Development (RD) Blocks were selected; Medziphema and Changtongya from Dimapur and Mokokchung districts and Peren and Jalukie from Peren district. Thirteen villages were selected from the RD Blocks based on the extent of pineapple cultivation. Under Dimapur, the villages of Molvom, Bungsang and Medziphema were selected; from Peren, the villages of Samzuiram, Mhainamtsi, Kejanglwa, Jalukie, Punglwa and Heningkunglwa; and from Mokokchung, Changtongya, Nukshiyim, Liroyim, and Yaongyimsen villages were selected. A proportionate random sampling method was followed, wherein 45 per cent of the total pineapple growers from the selected villages were included, resulting in a final sample size of 275 respondents.

Primary data were collected through a pre-tested interview schedule. The study assessed the adoption of sustainable agricultural practices among pineapple growers, grouped under four major dimensions: agronomic practices, resource management (soil, water and nutrients), pest and disease management and post-harvest management. An adoption index was developed to quantify the level of adoption. Scores of '2', '1' and '0' were assigned for full, partial and non-adoption, respectively. Based on the cumulative adoption scores, respondents were classified into three categories; low, medium and high adoption. A z-test was used to compare the adoption levels among the three districts.

To identify the determinants influencing the adoption of sustainable agricultural practices, Principal Component Analysis (PCA) method was applied. Components with eigenvalues $\geq$1 were retained. Variables with factor loadings $\geq$0.40 were retained for interpretation. Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity were applied to assess sampling adequacy.

RESULTS

Table 1 revealed the adoption index of sustainable pineapple cultivation practices across the selected districts. Under agronomic practices, full adoption of propagation (100.00%) was observed in all districts. Moderate adoption was recorded for land preparation and spacing, while nil (0.00%) adoption was observed for growth regulators and treatment of planting material in all districts. Under resource management practices, weed management showed 100.00 per cent adoption in all districts. Ratooning recorded adoption indices ranging from 80.36–87.50 per cent, whereas manuring, irrigation and cropping pattern exhibited low adoption indices. Under pest and disease management, biological method (0.00%) was not adopted in any district. Cultural methods showed very high adoption (94.05–97.78%), while physical methods were adopted moderately (36.19–52.78%) across the districts. Post-harvest management dimension had comparatively higher adoption among all the dimensions. 100.00 per cent adoption of post harvest management and storage was observed across districts. Whereas adoption of value addition practices ranged from 13.33–19.71%.

Table 1. Adoption Index of sustainable practices in pineapple cultivation among the selected districts

Dimensions of SAPs	Areas of Sustainable practices	Adoption Index (AI)			Overall
		Mokokchung	Dimapur	Peren	AI
Agronomic practices	Land preparation	62.5	54.00	54.64	55.09
	Varieties	58.33	54.28	59.64	56.09
	Propagation	100.00	100.00	100.00	100.00
	Spacing	55.83	59.43	52.14	57.18
	Plant population	49.17	52.00	41.43	49.00
	Planting material	49.17	49.28	48.93	49.18
	Treatment of planting material	0.00	0.00	0.00	0.00
	Growth regulators	0.00	0.00	0.00	0.00
Resource management (Soil, water and nutrient)	Manuring	21.67	7.05	4.76	8.06
	Cropping pattern	49.17	19.14	15.00	21.36
	Ratooning	87.5	82.00	80.36	82.18
	Irrigation	13.33	11.43	8.57	10.91
	Mulching	65.55	49.62	43.81	49.88
	Weed management	100.00	100.00	100.00	100.00
Pest and disease management	Biological method	0.00	0.00	0.00	0.00
	Cultural method	97.78	95.52	94.05	95.39
	Physical method	52.78	42.67	36.19	42.12
Post-harvest management	Harvesting	99.44	93.52	94.05	94.30
	Storage	100.00	100.00	100.00	100.00
	Post-harvest management	100.00	100.00	100.00	100.00
	Value addition	13.33	19.71	15.36	17.91

Table 2 showed that majority of the respondents (64.73%) were found under the medium adoption category, followed by high (19.63%) and low (15.64%) categories. Mokokchung recorded the highest mean adoption index (57.56), followed by Dimapur (52.47) and Peren (50.28). Z-test revealed significant differences in adoption indices between Dimapur and Peren ($z = 3.435$, $p<0.01$), Dimapur and Mokokchung ($z = 5.845$, $p<0.01$) and Peren and Mokokchung ($z = 7.334$, $p<0.01$).

Table 3 exhibited factors influencing the adoption of sustainable cultivation practices in pineapple. Factor analysis extracted eight factors with eigenvalues ≥1, explaining 62.49 per cent of the total variance (KMO = 0.728). Factor 1 (Land Use and Income) accounted for the highest variance (18.29%) and included variables, size of landholding under agriculture, land under pineapple cultivation, annual income, profitability, productivity and employment generated. Factor 2 (Motivational Factor) explained 10.30 per cent of the variance and included innovativeness, risk-bearing ability, market innovativeness, achievement motivation and scientific orientation. Factor 3 (Extension Access) contributed 7.48 per cent of the variance and comprised information sources utilization, productivity, extension contact and training exposure. The remaining factors were management and market awareness (6.36%), socio-economic participation (5.71%) socio-economic (5.36%), nutrient management (4.68%) and resource use efficiency (4.31%).

DISCUSSION

The adoption pattern observed in sustainable pineapple cultivation reflects farmers' preference for practices that are familiar, economically viable and compatible with existing farming systems. Practices that are simple, yield immediate benefits and low-risks

Table 2. District-wise Adoption Index and adoption level of sustainable pineapple cultivation practices

District	Low adoption (AI < 47.28)	Medium adoption (AI: 47.28 - 57.66)	High adoption (AI > 57.66)	Mean AI ± SD
Dimapur	26 (14.86)	115 (65.71)	34 (19.43)	52.47 ± 5.14[b]
Peren	17 (24.29)	48 (68.57)	5 (7.14)	50.28 ± 4.26[c]
Mokokchung	0 (0.00)	15 (50.00)	15 (50.00)	57.56 ± 3.86[a]
Overall (275)	43 (15.64)	178 (64.73)	54 (19.63)	52.47 ± 5.19

Note: Values under Low, Medium and High adoption are frequency followed by percentage in parentheses. Means followed by different superscripts are significantly different at the 1 per cent level based on pairwise z-tests

Table 3. Rotated factor matrices of the variables along with factor loadings, variance and factors renamed

Factors	Variables	Factor loading	% of variance explained	Cumulative % explained
Factor –1Land use and income	Size of landholding under agriculture (X_{13})	0.851	18.293	18.293
	Size of land under pineapple cultivation (X_{14})	0.915		
	Annual income (X_{15})	0.676		
	Profitability (X_{16})	0.652		
	Productivity (X_{17})	0.437		
	Employment generated (X_{18})	0.919		
Factor –2Motivational factor	Innovativeness (X_8)	0.647	10.299	28.592
	Risk bearing ability (X_9)	0.489		
	Market innovativeness (X_{10})	0.671		
	Achievement motivation (X_{12})	0.750		
	Scientific orientation (X_{27})	0.423		
Factor –3Extension access	Sources of information utilization (X_7)	0.782	7.481	36.073
	Productivity (X_{17})	0.435		
	Extension contact (X_{24})	0.785		
	Training exposure(X_{25})	0.425		
Factor –4Management and market awareness	Education (X_4)	0.433	6.357	42.430
	Market orientation (X_{20})	0.813		
	Management orientation (X_{21})	0.772		
Factor –5Socio-economic participation	Social participation (X_6)	0.503	5.707	48.138
	Decision making ability (X_{11})	0.651		
	Economic motivation (X_{19})	0.601		
Factor –6Socio-economic	Age (X_1)	0.809	5.355	53.493
	Family size (X_2)	0.598		
	Experience (X_{26})	0.693		
Factor –7Nutrient management	Economic motivation (X_{19})	0.435	4.681	58.174
	Integrated Nutrient Management (X_{23})	0.664		
Factor –8Resource use efficiency	Input self-sufficiency (X_5)	0.734	4.312	62.486
	IPM (X_{22})	0.521		
	Scientific orientation (X_{27})	0.519		
	Kaiser-Meyer-Olkin Measure	0.728		

tend to be more readily adopted, whereas technically demanding or input-intensive practices remain constraint by limited technical knowledge, input accessibility and perceived risks. Similar patterns were reported by Rizzo et al. (2024), Singh and Mazhar (2024) & Thangjam and Jha (2025) also reported low adoption of advanced agronomic and sustainable practices due to limited scientific guidance and training support. Mixed adoption of resource management dimension indicated resource related constraints. Labour requirements, cost and resource constraints, limited technical guidance and inadequate extension support may have probably led to low adoption of integrated management practices, as also observed in the study by Das et al. (2014) and Ekyaligonza et al. (2024). In pest and disease management, higher adoption of cultural and physical methods suggests farmers' inclination towards environmentally safe and low-cost practices. In contrast, zero adoption of biological method indicates gaps in awareness, training and access to effective bio-control agents (Russo et al., 2025). Very high adoption of post-harvest practices indicates familiarity with basic handling operations. The relatively limited engagement in value addition may be due to infrastructural, market linkage gaps and constraints in adopting value-added technologies as reported by Rai et al. (2023) and Kumar et al. (2025).

Significant variance in district-wise adoption analysis may be attributed to differences in resource base, exposure to extension services and institutional access. These findings underscore the need for enhancing adoption intensity across the districts through location-specific extension strategies.

Factor analysis revealed the multidimensional nature of adoption behaviour. The dominance of "land use and income" suggests that farmers with larger land holdings, higher income and profitability are more likely to adopt sustainable practices, emphasizing the role of economy capacity in technology adoption (Nadaf et al., 2025).

Notably, market orientation, extension contact and management orientation, which exhibited high factor loadings, are widely recognized as critical determinants of adoption behaviour. Farmers with stronger market orientation are better able to respond to market demand and price signals, thereby enhancing adoption of improved practices, particularly in emerging agricultural systems of Northeastern India where market linkages remain crucial (Das et al., 2015; Ghosal & Gangabhushan, 2024). Similarly, extension contact significantly influences adoption by improving access to information, training and technical support, as evidenced in studies on pineapple growers in Nagaland where information source utilization showed a strong positive association with adoption behaviour (Paramasivam et al., 2021; Pongener & Jha, 2024). In addition, higher management orientation enables farmers to plan resource use efficiently and make better production decisions, which has been identified as a key determinant of adoption of farm business and sustainable practices in Indian agriculture (Thakur et al., 2022). Furthermore, studies also highlight that variables such as training exposure, social participation and access to extension services significantly influence farmers' adoption behaviour and attitudes toward sustainable pineapple cultivation (Pongener & Jha, 2023 Kumar et al., 2025). These factors help explain the relatively higher adoption levels in Mokokchung.

Farmers with higher education, stronger managerial ability and market orientation were also more likely to adopt sustainable practices, consistent with Iticha and Taresa (2020). The identification of nutrient management and resource use efficiency as distinct factors further highlights the need for integrated approaches such as Integrated Nutrient Management (INM) and Integrated Pest Management (IPM). Empirical evidence indicates that INM enhances nutrient use efficiency, productivity and soil health (Meena and Suman, 2025), while IPM practices such as trap cropping in pineapple reduce pest incidence (Abdullah et al., 2024). Strengthening training and input access in these areas can improve sustainability and adoption intensity.

CONCLUSION

The study revealed uneven adoption of sustainable agricultural practices (SAPs) in pineapple cultivation across dimensions and districts. Post-harvest and agronomic practices showed relatively higher adoption compared to resource management practices, highlighting a need for targeted interventions in soil, water and nutrient management. Adoption behaviour was influenced by motivational attributes, economic factors and access to extension services, emphasizing the multidimensional nature of technology adoption. The inter-district variations in adoption further needs location-specific extension planning. Strengthening institutional support, improving extension services and capacity building particularly in promoting Integrated Nutrient Management (INM) and Integrated Pest Management (IPM) are vital for enhancing sustainable pineapple cultivation in Nagaland.

DECLARATIONS

Ethics approval and informed consent: Throughout the study, the respondents were asked for their informed consent.

Conflict of interest: The research was carried out without any financial or commercial ties that might be seen as a potential conflict of interest, according to the authors. The authors affirm that they carefully examined, amended and edited the content as necessary when preparing this work. The final content of this publication is entirely the authors' responsibility.

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Research Article

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Competency of Agripreneurs in Organic Farming: An Empirical Analysis on Palakkad District in Kerala

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HIGHLIGHTS

- Agripreneurial competencies among entrepreneurs in organic farming were found to be multidimensional in nature in Palakkad district.
- Agripreneurs exhibited adequate skill levels which positively reflected in their agripreneurial competencies and enterprise capabilities.
- Professional training, digital exposure and resource support are essential to strengthen competency levels of Agripreneurs in Palakkad.

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ABSTRACT

Organic farmers mainly relied on seasonal changes and ecological conditions in Kerala, as a result, entrepreneurs in the organic sector face several uncertainties in Kerala. Earlier research rarely analysed the skills and competencies of organic agripreneurs. The study analyses the dimensions of competency of organic agripreneurs in Palakkad district of Kerala. To accomplish this goal, a mixed-method approach was adopted. Primary data were collected through a structured interview schedule from 250 respondents in February 2026. The primary data were analysed using multinomial logit regression. The organic agripreneurs needed to improve their skill levels, which were reflected in their competency levels. It indicated that policy support mechanisms such as professional training, digital exposure and access to resources were essential for enhancing the competency levels of agripreneurs in organic sector.

INTRODUCTION

Organic farming has been emerged as a sustainable alternative to conventional methods of farming in Kerala. As a reflection of this shift, a notable portion of the total agricultural land has been brought under organic cultivation, reflecting a gradual shift towards eco-friendly farming practices. In Kerala, organic farming remains a fundamental sector, sustaining the livelihoods of a notable segment of the population. Despite its growing prominence, farmers and entrepreneurs in organic sector have been facing several challenges. They often encounter several constraints related to productivity, technical knowledge, and market access, which limit its long-term sustainability as a viable enterprise (Chopra & Rathore, 2024; Bhuriya & Gour, 2025; Kiran et al., 2025; Kerala Economic Review, Various Years). Palakkad was devoted a considerable portion of its total land to organic farming. In this context, agripreneurship in organic sector considers as an effective pathway for transforming agriculture into a market-oriented and income-generating enterprise. Government has introduced several initiatives to support organic farmers. Farmer Producer organisations (FPOs) supported these initiatives. In order to accelerate the impact of initiatives government, agripreneurs were expected to have a strong set of competencies (McElwee & Bosworth, 2010; Garima et al., 2023; Trivedi & Patel, 2024; Kerala Economic Review, Various Years).

Previous studies have examined various dimensions of agriculture enterprises and their agripreneurial attributes. Despite their considerable contributions, agripreneurs encounter multiple constraints, ranging from restricted access to resources and

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technology to skill mismatches and market imperfections. More specifically, previous findings rarely assessed specific competencies of successful organic agripreneurs. The absence of skills to agripreneurs often limits the ability of agriprenuers to identify opportunities and sustain agribusiness ventures (Gills et al., 2021; Gupta et al., 2023; Mukharjee & Ghosh, 2025). An in-depth analysis of the specific challenges faced by agripreneurs in organic sector is imperative for the formulation of evidence-based policies and interventions. It was aimed to empower agripreneurs and advancing sustainable agricultural development. In particular, the present study aimed to enquire the multidimensional competencies of organic agripreneurs in Palakkad district.

METHODOLOGY

The present study was both descriptive and analytical in nature. Palakkad occupied a substantial presence of farmers in organic agriculture in Kerala (Kerala Economic Review, Various Years). Palakkad was fixed as the sample district to analyse the skills of organic agripreneurs. Stratified random sampling was followed to identify the respondents. Palakkad was divided into Block Panchayats. Block panchayat has been divided into grama panchayats. From each panchayath, 5 respondents were planned and altogether 250 samples were selected. Accordingly, respondents were stratified based on their socio-economic characteristics. A structured questionnaire was used to collect the primary data. According to Cochran's formula for sample size determination, the required sample size depends on the confidence level, variability in the population, and the acceptable margin of error. Assuming a 95% confidence level (Z =1.96), maximum variability (p = 0.5), and a permissible error margin of 6 to 7%, the estimated sample size was approximately 200 to 270 respondents. The sample size was determined based on standard statistical equation. Accordingly, a sample size of 250 was considered for the present study. The equation is expressed in the following form:

$$N_0 = Z^2pq/e^2$$

Where, (N_0) =required sample size; (Z)=standard normal variate corresponding to the desired confidence level (1.96 at 95% confidence level); (p)=estimated proportion of the population possessing the attribute of interest; (q)=proportion of the population not possessing the attribute, calculated as (q=1-p); (e) = desired level of precision or margin of error.

An Agripreneurial Competency Scale (ACS) was used to fetch competency levels. This scale was developed through an extensive theoretical and empirical literature and expert discussions. Afterwards, competency indicators were identified and structured into five domains. They were: (i) personal and behavioural competencies; (ii) agribusiness management competencies; (iii) psychological competencies; (iv) strategic and modern competencies and (v) sustainability and innovation competencies. Each domain comprised multiple indicators representing specific skill dimensions. Based on these domains, 50 statements were developed. In total, the competency scale included 50 skill indicators. Equal weights were assigned to all competency indicators because each competency was considered equally important in evaluating agripreneurial capability. The score for each respondent was obtained by summing the scores across all 50 competency items. Based on these items, a questionnaire was developed. Respondents were classified into low, medium and high competency categories based on percentile distribution. A pilot study was conducted among respondents in the study. The validity of the research findings was ensured through a series of statistical procedures.

Subsequently, the reliability and clarity of the instrument was tested. The Cronbach's Alpha coefficient of the competency scale was 0.861. The adequacy of the data for factor analysis was tested using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity confirmed the adequacy and validity of the scale (Cronbach, 1951; Garcia, 2020). Finally, to identify the determinants of agripreneurial competency levels, a multinomial logit regression model was employed. Therefore, the findings of the study were derived from a statistically reliable and valid analytical procedure. The findings of the analysis are presented in the next section.

RESULTS

The socio-economic profile of the respondents revealed that male argipreneurs are 51.2% while female respondents constituted to 48.8%. Majority (47.2%) of the respondents belong to 26-35 age group which indicated the active youth segment in organic sector.

Results of the analysis on personal and behavioural competencies are presented in Table 1. It is seen that most of the agripreneurs had 'high' personal and behavioural competencies in Palakkad. For instance, 'decision-making competency' was recorded the highest proportion in the high category (54.4%), followed by 'continuous learning orientation' (49.6%) and 'creative problem-solving ability' (46.4%). It implied that the agripreneurs possesses the high ability to evaluate alternatives, learn from experience, and

Table 1. Personal, behavioural and agribusiness competencies of agriprenuers in Palakkad

	Item	Low	Medium	High
I	*Personal and Behavioural Competencies*			
1	Persistence	24.8	38.4	36.8
2	Social leadership ability	21.6	35.2	43.2
3	Communication competency	19.6	41.2	39.2
4	Relationship-building skill	22.4	36.0	41.6
5	Continuous learning orientation	17.6	32.8	49.6
6	Creative problem-solving ability	16.0	37.6	46.4
7	Innovative orientation	20.0	43.6	36.4
8	Analytical reasoning ability	23.6	40.8	35.6
9	Decision-making competency	15.2	30.4	54.4
10	Solution-oriented ability	18.4	37.6	44.8
II	*Agribusiness Management Competencies*			
1	Financial planning ability	22.8	37.6	39.6
2	Budgeting and cost control	20.4	38.8	40.8
3	Pricing strategy skill	18.4	35.2	46.4
4	Marketing and promotion ability	21.6	37.2	41.2
5	Supply chain coordination	24.0	36.0	40.4
6	Bargaining and negotiation skill	19.2	34.4	45.6
7	Inventory management ability	24.8	38.4	36.8
8	Market penetration ability	18.8	39.2	42.0
9	Resource allocation skill	22.0	38.0	40.0
10	Business risk management	20.8	36.0	43.2

respond effectively to emerging challenges, which in turn determined the strong behavioural readiness among agripreneurs. Similarly, skills such as social leadership ability (43.2%), relationship-building skill (41.6%), and solution-oriented ability (44.0%) also was high among respondents. These dimensions of competencies have played a crucial role in enterprise sustainability.

Entrepreneurs in organic agriculture remained in the 'medium' category was mainly in communication competency (41.2%) and innovative orientation (43.6%)**.** These findings suggest that 'low' category entrepreneurs will improve their traits by training and mentorship programmes. Results on agribusiness management are presented in Table 1. It is evident that pricing strategy skill shows the 'highest' **(**46.4%), category followed by bargaining and negotiation competency (45.6%)**,** business risk management (43.2), market penetration ability (42.0%). These relative strengths of these components show relatively strong market-oriented decision-making abilities. It was exhibited that 'moderate' competency levels are present in some skills such as budgeting and cost control (38.8%) and market penetration ability (39.2%). It indicates that the entrepreneurs are at an evolving and early stage of developing stronger managerial capabilities. In addition, inventory management ability (24.8%) and supply chain coordination (24.0%) showed relatively higher proportions in the low category.

Results on psychological competencies are presented in Table 2. A notable majority of entrepreneurs belong to 'high' competency category in most of the dimensions. For instance, 'achievement motivation' recorded the highest proportion (52.8%), followed by self-confidence (50.4%). It indicates that respondents possess confidence in their own abilities and clarity in pursuing entrepreneurial goals. Further, self- belief (49.2%) and goal-oriented approach (48.4%), are also exhibited 'high' among entrepreneurs. This reflects the ability of agripreneurs to adapt to uncertainty and

Table 2. Psychological and strategic and modern competencies

	Item	Low	Medium	High
III	*Psychological Competencies*			
1	Achievement motivation	16.4	30.8	52.8
2	Self-confidence	17.6	32.0	50.4
3	Emotional resilience	19.6	34.8	45.6
4	Stress management ability	23.2	36.8	40.0
5	Goal orientation	18.0	33.6	48.4
6	Entrepreneurial mindset	19.2	36.0	44.8
7	Calculated risk-taking	15.6	37.6	46.8
8	Self-control orientation	21.6	38.4	40.0
9	Adaptive resilience	18.4	35.2	46.4
10	Self-belief competency	16.8	34.0	49.2
IV	*Strategic and Modern Competencies*			
1	Opportunity identification skill	15.2	34.4	50.4
2	Business planning competency	18.4	32.8	48.8
3	Demand anticipation skill	20.0	36.4	43.6
4	Situational awareness ability	16.8	31.2	52.0
5	Information acquisition skill	14.8	34.0	51.2
6	Digital promotion competency	23.2	38.0	39.2
7	Agri-tech adoption ability	20.8	36.0	43.2
8	Strategic forecasting ability	19.2	36.8	44.0
9	Competitive intelligence	21.6	37.6	40.8
10	Innovation planning skill	18.4	35.6	46.0

Table 3. Sustainability and innovation competencies

	Item	Low	Medium	High
V	*Sustainability and innovation competencies*			
1	Sustainable resource utilization	19.2	39.2	42.4
2	Eco-friendly farming orientation	22.4	36.8	40.8
3	Waste management skill	25.6	38.4	36.0
4	Renewable technology awareness	23.2	35.2	42.0
5	Sustainable market linkage	20.8	37.6	41.6
6	Innovation diffusion ability	16.4	36.4	47.2
7	Climate adaptation planning	22.8	34.4	42.8
8	Green entrepreneurship orientation	19.2	35.2	46.0
9	Sustainable input management	22.0	38.0	40.0
10	Resource conservation skill	20.0	36.0	44.0

Source: Authors computed from primary data

manage the risks associated with agribusiness activities. Resilience has been widely recognized as a key factor in positive youth development and enterprise sustainability. However, relatively higher shares in the 'low' category were observed for stress management ability (23.2%) and self-control orientation (21.6%).

Dimensions such as situational awareness ability belong to the 'high' share in the high category (52.0%), followed by information acquisition competency (51.2%). This suggests that the respondents are capable of identifying market opportunities and responding to dynamic agricultural conditions. Similarly, opportunity identification (50.4%) and business planning competency (48.8%) also show a notable concentration in the 'high' category. These findings imply that entrepreneurs possess the ability to formulate enterprise strategies and align innovation. These results revealed that agripreneurs demonstrated relatively higher competency levels in agri-tech adoption ability (43.2%) and strategic forecasting ability (44.0%), indicating growing adaptability towards modern agricultural practices.

However, digital promotion competency recorded relatively higher (38.0%) quotient among organic agricultural entrepreneurs in Palakkad. From the Table 3, it is evident that innovation diffusion ability records the highest share in the high category (47.2%) followed by green entrepreneurship orientation (46.0%) while sustainable resource utilization account only 41.6%. These findings imply that the respondents demonstrate a positive attitude towards traits such as efficient resource use, climate resilience, and environmentally responsible enterprise practices. However, certain areas such as waste management skill show a relatively higher proportion in the 'low' category (25.6%), It indicates that practical knowledge related to waste recycling requires improvement. Subsequently, the present research attempted to extract the summary of agripreneurial competencies. In this analysis, factor analysis was employed to identify the major dimensions of agripreneurial competencies.

Exploratory factor analysis (EFA) using principal component analysis (PCA) extraction method with varimax rotation was employed to identify the major dimensions of agripreneurial competencies. Variables with factor loadings 'above 0.50' were retained for interpretation. The extracted factor structure confirmed the existence of five major competency dimensions among agripreneurs in organic farming. The summary results of the analysis

Table 4. Summary of extracted factors of agripreneurial competencies

No.	Factor	No. of Variables	Eigen Value	Variance Explained (%)	Cumulative Variance (%)
I	Personal and Behavioural Competencies	10	5.842	21.36	21.36
II	Agribusiness Management Competencies	10	4.716	17.24	38.60
III	Psychological Competencies	10	3.928	14.36	52.96
IV	Strategic and Modern Competencies	10	3.214	11.75	64.71
V	Sustainability and Innovation Competencies	10	2.120	7.75	72.46

are exhibited in Table 4. It is clear that there are 50 skill variables grouped into five distinct factors. Personal and behavioural competencies, has an eigenvalue of 5.842 and explained 21.36% of the total variance, making it the most dominant factor. Agribusiness management competencies, explain 17.24% of the variance with an eigenvalue of 4.716. Similarly, psychological competencies, strategic and modern competencies, and sustainability and innovation competencies explain 14.36%, 11.75%, and 7.75% of the variance respectively. Factors with an 'eigenvalue' greater than 1 are considered statistically significant and suitable for retention. The cumulative variance explained by the five factors is 72.46%, which is also considered satisfactory. Since all the extracted factors have eigenvalues higher than 1, the factor structure is considered statistically valid and meaningful. Thus, results confirmed that the identified competency domains are statistically reliable and suitable for further empirical analysis.

Based on the results, it was noticed that these domains are responsible for 72.46% of the total variance. Subsequently, it was necessary to apply The Kaiser-Meyer-Olkin (KMO) to measure the adequacy of samples in the present investigation. The Kaiser-Meyer-Olkin (KMO) measure is used to assess the adequacy of the sample for factor analysis (Garcia, 2020; Goretzko & Ruscio, 2024). The KMO value is 0.842. It indicates that the variables included in the study share sufficient common variance for extracting meaningful factors. The calculated chi-square value is 2156.38 with 300 degrees of freedom. The significance value is 0.000, which is less than the conventional 5% level of significance. It indicates that the variables are significantly correlated and suitable for factor extraction. Therefore, the null hypothesis stating that the correlation matrix is an identity matrix was rejected. Hence, the KMO and Bartlett's test results confirm the adequacy and validity of the data for conducting exploratory factor analysis.

These extracted factors provide a strong conceptual foundation for understanding the multidimensional nature of agripreneurial skills among entrepreneurs in organic farming. The Multinomial logistic regression is an appropriate statistical tool when the dependent variable consists of more than two unordered categories. The model was employed to identify the factors influencing medium and high agripreneurial competency levels, taking the low competency group as the reference category. Results of estimated multinomial logit coefficients are exhibited in Table 5. It was revealed that training exposure has a positive and statistically significant effect on both medium and high competency levels, with odds ratios of 2.147 and 1.912, respectively. It indicates that trained respondents are more

Table 5. Estimated multinomial logit coefficients of factors influencing agripreneurial competency

Skill Level	Explanatory Variables	B	Std. Error	Sig.	Exp (B)	95% Confidence Interval for Exp (B)	
						Lower	Upper
Medium	Intercept	18.624	3.842	.000			
	Age	-0.168	0.298	.573	0.845	0.471	1.518
	Farming experience	-0.087	0.041	.034	0.917**	0.846	0.995
	Training exposure	0.764	0.284	.007	2.147*	1.231	3.744
	Digital media exposure	0.582	0.236	.014	1.790**	1.128	2.841
	Landholding status	0.438	0.198	.027	1.550**	1.052	2.283
	Access to institutional credit	0.392	0.181	.031	1.480**	1.038	2.111
	Annual farm income (Low)	-3.862	1.145	.001	0.021*	0.002	0.196
	Annual farm income (Medium)	-2.914	1.082	.007	0.054*	0.006	0.462
	Low income from agri-enterprise	-18.764	1.526	.000	<.001*		
High	Intercept	21.358	2.116	.000			
	Age	0.294	0.176	.095	1.342***	0.949	1.897
	Farming experience	0.118	0.049	.016	1.125**	1.022	1.239
	Training exposure	0.648	0.221	.003	1.912*	1.239	2.949
	Digital media exposure	0.405	0.168	.016	1.499**	1.078	2.083
	Landholding status	0.486	0.193	.012	1.626**	1.114	2.372
	Access to institutional credit	0.537	0.214	.012	1.711**	1.124	2.604
	Annual farm income (Low)	-4.624	1.287	.000	0.010*	0.001	0.088
	Annual farm income (Medium)	-3.508	1.104	.001	0.030*	0.004	0.221
	Low income from agri-enterprise	-19.864	1.542	.000	<0.001*		

likely to attain higher competency levels. Similarly, digital media exposure exerts a positive and significant influence in both categories. It suggests that access to online information and digital platforms improves agripreneurial competencies.

Further, landholding status and access to institutional credit show positive and significant coefficients. It implies that productive assets and financial support enhance the probability of achieving better competency levels. Farming experience exhibits a negative but significant effect in the medium category and a positive significant effect in the high category. It advocates that greater practical exposure strengthens advanced competency levels over time. The coefficients of annual farm income (low and medium) are negative and statistically significant in both categories. This evidence supports that respondents with lower income are less likely to attain higher competency groups. Most importantly, findings confirmed that variables such as training, digital exposure, financial access, and resource ownership are major factor which influenced them. These factors would have positively influence agripreneurial competency levels.

DISCUSSION

Results indicate that behavioural characteristics such as decision-making ability, and problem-solving skills play a critical role in shaping agripreneurial capacity. In addition, factors such as training, digital exposure, continuous learning orientation, financial access, and resource ownership were positively influenced competency levels of entrepreneurs in organic farming. These findings seem to be mentioned in the previous literature on entrepreneurial success. For instance, entrepreneurial success is rooted in behavioural attributes and competencies at the personal level especially in rural contexts (Yi et al., 2023; Kumar et al., 2025; Siddiqui & Rokade, 2026).

'Agribusiness management competency' is a major factor in determining entrepreneurial performance in organic farming. This finding seems to be indirectly validated by the previous literature on agribusiness management competencies, particularly in pricing strategy, negotiation skills, and risk management (Toledo-López et al., 2012; Raina et al., 2016; Garima et al., 2023; Suman et al., 2025).

Research inferred that psychological competencies can reinforce the internal motivation in agripreneurship. Agripreneurial performance require psychological traits such as motivation, self-confidence and resilience. This finding seems to be similar in some of the earlier findings on entrepreneurial competency. For instance, earlier research argues that traits such as self-efficacy, self-control, emotional regulation skills. optimism, and resilience would enhance entrepreneurial outcomes (Luthans & Youssef-Morgan, 2017; Ismail et al., 2023; Kademani et al., 2024; Kesari et al., 2024; Kademani et al., 2026).

It was revealed that strategic and modern competencies are relatively well-developed among the argipreneurs in Palakkad. This reflects an increasing adaptability to execute dynamic agricultural environments with respect to evolving market conditions. These findings are implied in the previous literature on competency of entrepreneurs and their performance (Klerkx et al., 2019; Garima et al., 2023).

Finally, this study found that sustainability and innovation competencies have a positive orientation towards environmentally responsible agribusiness practices. In particular, organic agripreneurs require competencies such as system certifications, traceability mechanisms and sustainable farm management practices. High levels of green entrepreneurship orientation and innovation diffusion ability indicate a growing awareness of sustainable agriculture and climate-resilient practices. Some previous findings implicitly mentioned on interrelationship between entrepreneurial performance and sustainability management practices (Gills et al., 2013; Chouaibi et al., 2022; Cornejo et al., 2024).

Apart from these insights on competencies, this study attempted to identify the determinants of these competencies. It was revealed that factors like such as training exposure to structured skill development programmes and digital media exposure are essential. In addition, economic characteristics such as landholding status and access to institutional credit have shown a strong and positive association with competency levels. Unsurprisingly, inadequate income from agri-enterprise exhibits a strong negative effect. It indicated that financial constraints significantly limit the upward mobility of agripreneurs. These findings appear to be supported by the previous revelations on entrepreneurial performance and its determinants (Nain et al., 2018; Kobba et al., 2021; Bahaw et al., 2024; Kljucnikov et al., 2025).

CONCLUSION

A considerable proportion of respondents were found to have high competency levels. However, certain areas such as stress management ability, waste management skill, and digital promotion competency require further improvement. The major determinants that which influence the competency levels are training exposure, digital media exposure, landholding status, farming experience, and access to institutional credit. In a nutshell, the present study demonstrates that agripreneurial competencies are shaped by a complex interaction of behavioural traits, psychological factors, strategic capabilities, and socio-economic conditions. While the findings indicate a favourable competency base among entrepreneurs in organic sector, the presence of moderate-level competencies across several dimensions suggest that agripreneurship requires urgent attention. Therefore, present research suggests that policy interventions focusing on skill development, digital empowerment, financial inclusion, and practical training are inevitable and urgent.

DECLARATIONS

Ethics approval and informed consent: Informed consent was obtained from all respondents during the course of the research. Participation in the research was voluntary, and confidentiality of the information provided by the respondents was maintained throughout the investigation.

Conflict of interest: The authors declare that there is no conflict of interest regarding the publication of this paper. The research was conducted in the absence of any commercial or financial relationships that could be interpreted as a potential conflict of interest.

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Adoption of Climate-Resilient Technology by smallholder farmers in Rice-Based Cropping System in Western Central Table Zone of Odisha

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HIGHLIGHTS

- Intervention farmers showed higher technology adoption than control farmers and Annual income was significantly higher among intervention farmers.
- Innovativeness and occupation were the strongest direct predictors of climate-resilient technology adoption.
- Social participation exerted the highest indirect influence on adoption, mediated through innovativeness.
- Institutional access crop insurance and custom hiring centres significantly widened the intervention–control adoption gap.

ARTICLE INFO

Keywords: Climate-resilient technologies, Smallholder farmers, Technology adoption, Rice-based cropping systems, Extension services, Innovativeness, Odisha.

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ABSTRACT

Rice cultivation in rain-fed systems of Odisha is highly vulnerable to climate variability, threatening the livelihoods of smallholder farmers. This study assessed the adoption of Climate Resilient Technologies (CRTs) among smallholder farmers during Kharif 2023-24 in Jharsuguda district under the Western Central Table Land Zone of Odisha. A multi-stage sampling technique was employed to select respondents from intervention and control villages, with 60 farmers selected from each group. Adoption was evaluated across four modules: natural resource management, crop production, livestock and fisheries, and institutional interventions. Results showed that intervention farmers had significantly higher overall adoption levels than control farmers ($Z = 11.34$, $p < 0.01$). Adoption rates for drought-tolerant varieties, seed treatment, and crop insurance were notably higher among intervention farmers (86.67%) compared to control farmers (43.33%). Intervention farmers also recorded significantly higher annual income ($U = 5306$, $p < 0.05$). Multiple linear regression and path analysis identified innovativeness, occupation, farming experience, age, social participation, and farm size as key determinants of adoption. The study highlights the importance of ICT-based participatory approaches and strengthened institutional access for enhancing resilience in rice-based farming systems in Odisha.

INTRODUCTION

Rice (*Oryza Sativa* L.) is the main staple crop and a significant contributor to the agricultural economy of Odisha, grown on 4.61 million ha and produced 9.21 million tonnes in 2022–23 (Directorate of Agriculture, Govt. of Odisha, 2023). The state is predominantly an agricultural state with a share of almost 70% of Gross Cropped

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Area under rice cropping system and plays a significant role in rural livelihoods (Directorate of Agriculture, Government of Odisha, 2023). In less productive areas, diversified agriculture, like rice-pulse and rice-vegetables, has been encouraged to increase the income stability of farmers (Naik et al., 2025b; Rao et al., 2016). Rice production, however, has been impacted by the growing climate variability in Odisha, such as irregular rainfall, droughts, floods and long spells of dry weather (Lenka, 2023). In India, agriculture losses due to climate change in 2016-21 have been estimated at US$ 3.75 billion, and losses in agrarian productivity in the drought prone districts of Odisha could be as much as 40% less than the state average (Odisha Economic Survey 2023-24). In high temperature stress districts like Jharsuguda, there is likely to be an increase in production risks due to higher temperature (IPCC, 2021). In response to these challenges, the National Innovations on Climate Resilient Agriculture (NICRA) has encouraged the adoption of climate-resilient technologies such as drought-tolerant varieties, integrated nutrient management, and moisture conservation methods (National Innovations on Climate Resilient Agriculture, 2021). Previous research indicated that these technologies are effective in promoting productivity and income generation; with social participation, extension contact, and demonstration learning effecting adoption behaviour (Rogers, 2003; Sultana et al., 2020; Harikrishna & Naberia, 2021; Shanabhoga et al., 2023).

The study examined the status of adoption of 30 climate-resistant technology (CRT) across four modules (Reddy et al., 2025), its economic implications, and factors associated with the adoption behaviour of rice farmers in Jharsuguda based on correlation analysis, regression analysis and path analysis. Despite growing evidence on CRT adoption under NICRA, comparative empirical studies examining both adoption levels and their determinants across intervention and control groups within a single agro-climatic zone remain limited in Odisha (Naik et al., 2025b). This study, therefore, aimed to (i) assess the status of CRT adoption across four modules in Jharsuguda district during Kharif 2023–24, (ii) examine the economic implications of adoption on annual farm income, and (iii) identify key socio-personal, economic, communicational, and psychological determinants of CRT adoption among smallholder rice farmers. Two null hypotheses on adoption and income differences between intervention and control groups were tested.

METHODOLOGY

This study was carried out, in the Western Central Table Zone of Odisha in Jharsuguda district between 21°-22° N latitude and 83°-84° E longitude at an altitude of 225-280 m above mean sea level. The district is a kharif rice monoculture system where almost 78% of the gross cropped area is under Kharif rice production and is highly sensitive to rainfall deficiency in the critical growth stage of the rice crop (mid-July to mid-August), as reported by Mansingh et al. (2024). The respondents were selected using a multistage sampling design. The district of Jharsuguda was purposively selected as the district was considered to be more vulnerable in climatic condition and intervention and control villages under the National Innovations on Climate Resilient Agriculture programme were present there. Two intervention villages (Tharkuspur and Bhoimunda) and two similar non-intervention villages Telidihi and Luisingha located under Krishi Vigyan Kendra Jharsuguda and Odisha University of Agriculture and Technology were selected. One hundred and twenty farming households were randomly selected across two groups (intervention and control) with 60 farming households selected in each group. Primary data was gathered by conducting interviews, using a structured and face-to-face approach during kharif 2023-24. Adoption was measured using a three-point scale (0 = non-adoption, 1 = partial, 2 = full adoption) across 30 CRT practices (maximum score = 60). Categories were derived using the mean ± SD method. Content validity was ensured through expert validation and pilot testing with 20 farmers from an excluded village. A total of 14 independent variables were explored in four dimensions (socio-personal, socio-economic, socio-communication and socio-psychological) with over 30 Climate Resilient Technology (CRT) practices across four Modules (natural resource management, crop production, livestock and fisheries, and institutional interventions) (Sarkar et al., 2022; Sodhi et al., 2023). Both null hypotheses are now explicitly stated at the end of the Introduction/Methodology transition: H_1 (no significant difference in CRT adoption between groups) and H_2 (no significant difference in annual income).

The study employed descriptive and inferential statistics to analyse the relationship between the factors of the farmers' profile and the adoption of the technologies and practices of adaptation to climate change. All association and differences between variables were statistically analysed using Pearson's correlation and Z-test, and for ordinal income data the Mann–Whitney U test was performed. The effect of all 14 predictors was investigated by Multiple Linear Regression with enter and stepwise procedure (Yadav & Gosh, 2023). Both direct and indirect effects were estimated and Variance Inflation Factor (VIF) was used to check multicollinearity with all values being below 5. IBM SPSS Statistics was used for statistical analysis.

RESULTS

The implementation of technologies promoting resilience to climate change were covered under every module

The complete 30 adopted CRT Practices by Module is shown in Table 1. During Module I (Natural Resource Management), the intervention farmers reported significantly high percentage for full adoption of crop residue incorporation (56.67% vs 35.00%), soil sample collection and testing (48.34% vs 30.00%) and green manuring with Dhaincha in rice (38.33% vs 23.33%). Regarding Module II (Crop Production), the system that showed that the biggest difference (51.67% vs. 31.67%) was for the varieties of Drought-tolerant Rice. Adoption of individual intervention practices has significantly varied between intervention and non-intervention farms, with the adoption rate of 55.00%, 56.67% and 50.00% for weeding, seed treatment and intercropping, respectively. In Module IV (Institutional Interventions), village weather station access was reported by 45.00% of intervention farmers compared to 0.00% of control farmers, consistent with NICRA programme objectives. Crop insurance coverage under the *Pradhan Mantri Fasal Bima Yojana* (PMFBY) was also significantly higher in case of intervention farmers compared to the control farmers (86.67% vs. 43.3).

Table 1. Major climate-resilient technology interventions under different modules implemented among smallholder farmers in the study area

Module	Technologies/Practices
I: Natural Resource Management (In-situ Moisture Conservation)	Green manuring (Dhaincha) in rice, enriching soil by incorporating crop residues, renovation of community/ farm ponds, soil sample collection and testing, use of vermicomposting, mulching in vegetable crops
II: Crop Production	Drought-tolerant/disease-resistant rice variety, inter-cropping, hybrid maize/sweet corn variety cultivation, integrated nutrient and crop management, high-yielding disease-resistant vegetable growing, crop diversification, micronutrient application in cauliflower, seed treatment, paddy straw mushroom cultivation, micro-irrigation (drip and sprinkler), sowing of latest released varieties, weed management practices
III: Livestock and Fisheries	Urea treatment of fodder, deworming and vaccination, mineral mixture feed, fodder production and silage making, low-cost goat shed/cattle shed, integrated farming approach (fodder production)
IV: Institutional Interventions	Village fodder bank/seed bank, climate literacy via village weather station, custom hiring centre, use of ICT tools for climate risk mitigation, crop insurance through PMFBY

Table 2. Annual income distribution of intervention and control farmers (Jharsuguda district)

S. No.	Income category	Intervention (%)	Control (%)
1	Below Rs. 1,20,000	23.33	38.34
2	Rs. 1,20,001 to Rs. 2,40,000	46.67	43.33
3	Above Rs. 2,40,000	30.00	18.33
	Test Statistic	Value	
	Mann-Whitney U	5306.00	
	Wilcoxon W	124.00	
	Z Value	–1.54	
	Asymptotic Significance (2-tailed)	$p < 0.05$	

Note: Mann–Whitney U = 5306; $p < 0.05$.

Annual income distribution and economic implications

Table 2 reveals, that the proportion of the farmers in intervention group who got income above Rs. 2.40 lakh per year was 30.00% as against 18.33% of the control farmers. On the other hand, the proportion of farmers who became less than Rs. 1.20 lakh was 38.34% for the control farmers while it was 23.33% for the intervention farmers only. The Mann–Whitney U test showed that the income difference between the two groups was statistically significant (U = 5306, $p < 0.05$), allowing H_2 to be rejected and a measurable economic benefit of CRT adoption established.

Overall adoption level

Table 3 shows that 53.34% of intervention farmers were categorised as high adopters compared to 16.66% of control farmers, a difference of 36.68 percentage points. The Z-test value (Z = 11.34, $p < 0.01$) far exceeded the critical value of ±1.96, firmly rejecting H_o. The mean adoption score of intervention farmers (60.73) was 21.6% higher than that of control farmers (49.95).

Table 3. Distribution of respondents by overall adoption level of technologies

Category	Intervention (%)	Control (%)	Z-value
Low	20.00	46.67	
Medium	26.67	36.67	11.34**
High	53.34	16.66	
Mean	60.73	49.95	
SD	4.86	5.53	

Note: **Significant at p=0.01; critical Z = ±1.96; SD = standard deviation

Determinants of adoption: Correlation, regression, and path analyses

Table 4 shows the results of bivariate correlation. The strongest negative association was with age (r = "0.392, $p < 0.01$) and strong positive correlations were with innovativeness. The narrative has been corrected to read "strong positive correlations were with innovativeness (r = 0.386) and occupation (r = 0.363). Farm size (r = 0.281, $p < 0.01$), livelihood diversification (r = 0.268, $p < 0.01$), and economic motivation (r = 0.250, $p < 0.01$) also recorded significant positive associations No significant relationships were found between mass media exposure (r = 0.175), farming experience (r = 0.168) and education (r = 0.014) and adoption.

The Multiple Linear Regression (MLR) model (Table 5) explained 59.0% of the variance in adoption ($R^2 = 0.590$, F = 10.778, $p < 0.01$). Occupation (b = 3.599, $p < 0.001$), farming experience (b = 2.304, $p < 0.01$), and innovativeness (b = 0.788, $p < 0.01$) were significant positive predictors, while age exerted a strong negative effect (b = –3.832, $p < 0.01$). Table 6. Showed six variables namely occupation (X_4), innovativeness (X_{14}), age (X_1),

Table 4. Bivariate correlation of profile characteristics with adoption of technologies

Code	Variable	r-value	p-value
X_1	Age	–0.392**	0.000
X_2	Education	0.014NS	0.877
X_3	Farm size	0.281**	0.002
X_4	Occupation	0.363**	0.000
X_5	Annual income	0.194*	0.033
X_6	Farming experience	0.168NS	0.066
X_7	Irrigation status	0.209*	0.021
X_8	Livelihood diversification	0.268**	0.003
X_9	Social participation	0.234*	0.011
X_{10}	Mass media exposure	0.175NS	0.054
X_{11}	Extension contact	0.234*	0.011
X_{12}	Economic motivation	0.250**	0.006
X_{13}	Risk orientation	0.223*	0.014
X_{14}	Innovativeness	0.386**	0.000

Note: *Significant at $p < 0.05$; **Significant at $p < 0.01$; NS = Non-significant

Table 5. Multiple linear regression: Predictors of technology adoption

Code	Variable	b	SE	t-value	p-value
X_1	Age	–3.832**	1.029	–3.724	0.000
X_2	Education	–0.005NS	0.444	–0.010	0.992
X_3	Farm size	1.129*	0.467	2.416	0.017
X_4	Occupation	3.599***	0.876	4.109	0.000
X_5	Annual income	0.064NS	0.922	0.070	0.945
X_6	Farming experience	2.304**	0.818	2.816	0.006
X_7	Irrigation status	0.649NS	0.818	0.794	0.429
X_8	Livelihood diversification	1.047NS	0.834	1.255	0.212
X_9	Social participation	0.653*	0.294	2.222	0.028
X_{10}	Mass media exposure	0.193NS	0.230	0.838	0.404
X_{11}	Extension contact	0.195NS	0.189	1.033	0.304
X_{12}	Economic motivation	0.255NS	0.149	1.716	0.089
X_{13}	Risk orientation	0.028NS	0.147	0.192	0.848
X_{14}	Innovativeness	0.788**	0.253	3.117	0.002

Model fit: R = 0.768; R^2 = 0.590; Adjusted R^2 = 0.535; F = 10.778; $p < 0.01$.

Note: *p < 0.05; **p < 0.01; ***p < 0.001; NS = Non-Significant, b: Beta Co-efficient, SE: Standard error.

Table 6. Stepwise Regression- Parsimonious Predictors of CRT Adoption

Model	Predictors in Model	R	R^2	Adj.R^2	Std. Err.	New Predictor	B	β	t	Sig.
1	X_4	0.363	0.132	0.125	7.22	X_4	3.599	0.363	4.109	<.001
2	X_4-X_{14}	0.503	0.253	0.240	6.78	X_{14}	0.788	0.304	3.117	0.002
3	X_4-X_{14}-X_1	0.617	0.381	0.363	6.22	X_1	–3.832	–0.287	–3.724	<.001
4	X_4-X_{14}-X_1-X_6	0.679	0.462	0.440	5.84	X_6	2.304	0.245	2.816	0.006
5	X_4-X_{14}-X_1-X_6-X_9	0.713	0.509	0.484	5.61	X_9	0.653	0.192	2.222	0.028
6	X_4-X_{14}-X_1-X_6-X_9X_3	0.736	0.541	0.512	5.46	X_3	1.129	0.175	2.416	0.017

Final model: R = 0.736; R^2 = 0.541; Adj. R^2 = 0.512; F = 13.02; $p < 0.01$. All VIF values < 1.3.

Table 7. Path coefficients: Direct, indirect, and residual effects on adoption

Variable	Direct effect	Indirect effect	Sub-effect I	Sub-effect II	Sub-effect III
Age (X_1)	–3.832**	–0.620	0.376 (X_6)	0.020 (X_{14})	0.006 (X_9)
Education (X_2)	0.014NS	0.044	0.044 (X_{11})	0.026 (X_6)	0.016 (X_5)
Farm size (X_3)	1.129*	0.212	0.039 (X_7)	0.022 (X_8)	0.019 (X_{14})
Occupation (X_4)	3.599**	0.179	0.058 (X_{11})	0.049 (X_9)	0.032 (X_{14})
Annual income (X_5)	0.064NS	0.087	0.119 (X_6)	0.071 (X_2)	0.045 (X_{14})
Farming experience (X_6)	2.304**	0.098	0.008 (X_7)	0.005 (X_8)	0.003 (X_{14})
Irrigation status (X_7)	0.649NS	0.024	0.087 (X_9)	0.032 (X_{14})	0.021 (X_{12})
Livelihood diversification (X_8)	1.047NS	0.022	0.048 (X_4)	0.039 (X_{11})	0.025 (X_{14})
Social participation (X_9)	0.653*	0.458	0.176 (X_{14})	0.051 (X_{10})	0.040 (X_{12})
Mass media exposure (X_{10})	0.193NS	0.038	0.067 (X_{14})	0.037 (X_{11})	0.030 (X_9)
Extension contact (X_{11})	0.195NS	0.151	0.058 (X_{14})	0.055 (X_4)	0.033 (X_9)
Economic motivation (X_{12})	0.255NS	0.034	0.031 (X_{14})	0.030 (X_9)	0.025 (X_6)
Risk orientation (X_{13})	0.028NS	0.224	0.140 (X_{14})	0.050 (X_9)	0.040 (X_2)
Innovativeness (X_{14})	0.788**	0.058	0.036 (X_9)	0.035 (X_4)	0.028 (X_{11})

Note: *p < 0.05; **p < 0.01; NS = Non-Significant. Highest direct effect: Innovativeness (X_{14}). Highest indirect effect: Social participation (X_9).

farming experience (X_6), social participation (X_9) and farm size (X_3) were selected by stepwise regression to explain 54.1% of variance in adoption (Adjusted R^2 = 0.512, and F = 13.02, $p < 0.01$). All the Variance Inflation Factor (VIF) values were less than 1.3 and thus no multicollinearity was found.

The path analysis (Table 7) showed that the variable with the greatest direct effect on the adoption of technologies was innovativeness (X_{14}; 0.788), while the top indirect effect was provided by social participation (X_9; 0.458), followed by innovativeness (X_{14}; 0.176), and economic motivation (X_{12}; 0.040). Farming experience (X_6) and occupation (X_4) also had significantly direct effects. To capture the variance in adoption account for by factors not included in the model, the residual path coefficient was 0.641, which represented about 41% of the variance in adoption.

DISCUSSION

The foregoing shows that there was a positive contribution to technology adoption through structured extension support provided

under the NICRA programme, as the higher adoption of Climate Resilient Technologies (CRTs) by intervention farmers (Oraon et al., 2020; Meena et al., 2023). Crop residue incorporation and soil testing rates are on the rise, aligning with the soil health management guidelines recommended by the National Food Security Mission (Government of India, 2023). The same results were found by Nyasimi et al. (2017) who found that extension-based interventions increased NRM adoption by smallholders.

The fact that intervention farmers have also accepted the use of drought-tolerant varieties of rice also attests the success of demonstration-based varietal promotion from KVK Jharsuguda. In Odisha, improved varieties like Sahabhagi Dhan, Swarna Sub-1 and other drought stress tolerant varieties have recorded better yield performance during drought (Directorate of Agriculture, Government of Odisha, 2023; Odisha Economic Survey, 2023-24). Crop insurance enrolment, custom hiring centres etc. further reinforced the uptake of technologies, as noted by Pabba et al. (2022) and Sodhi et al. (2023). The economic analysis showed that the annual farm income of the CRT adopters was relatively high, and a significant portion of intervention farmers fell in the Rs. 2.40 lakh income bracket, which suggests a gradual shift towards diversification and enhancing livelihood stability (Odisha Economic Survey, 2023–24). The same positive gains in income are found in Assam and Rajasthan, thanks to climate-resilient practices (Sultana et al., 2020; Kalash et al., 2023; Yadav & Ghosh, 2034).

Socio-psychological variables identified, as the strongest predictor of adoption was the innovativeness which is in accordance with Rogers' (2003) Diffusion of Innovations theory. Direct and indirect effects were estimated through path analysis by decomposing standardised regression coefficients; indirect effects were computed as the product of standardised path coefficients along each causal pathway (Das et al., 2020).Innovativeness is linked to information-seeking behaviour and risk tolerance (Rogers, 2003); age is associated with cognitive inertia and physical constraints; social participation enhances adoption indirectly through peer learning and confidence-building. However, occupation had a positive effect on adoption, while age had a negative effect, suggesting that the farmers' age is associated with lower adoption rates (Harikrishna & Naberia, 2021; Bodsa & Chavda, 2024). No significant direct effects were found for education, farming experience and mass media exposure, indicating that passive access to information is not sufficient for adoption. Jena et al. (2023) have found that demonstration-based and personalised extension methods are effective in increasing the awareness of farmers and users, whereas using the media alone is ineffective. Increased innovativeness and economic motivation due to social participation contributed to indirect impact on adoption, suggesting the importance of farmer groups and local institutions in promoting peer learning and technology acceptance (Nyasimi et al., 2017; Kakoti et al., 2026). Other unexplained variations imply that other factors, including market access, credit availability, and input supply systems, also have an impact on adoption behaviour and need to be explored further (Naik et al., 2025a; Rahmawati et al., 2026).

CONCLUSION

The study revealed significant positive effects of structured exposure to climate-resilient technologies on both adoption behaviour and annual income of smallholder rice farmers in the Western Central Table Zone of Odisha. The strongest direct influences were found for innovativeness, while the strongest indirect influences were found for social participation and its association with innovativeness. The results underline the importance of participatory and farmer-to-farmer and community-based extension, instead of the more traditional passive dissemination. The policy recommendations are covering more farmers under crop insurance schemes, improving custom hiring centres, setting up of village level weather stations connected with mobile advisory services and integration of climate literacy aspects in the training at Krishi Vigyan Kendra. Building the capacity of farmer producer organisations and self-help groups can further contribute to social inclusion, climate resilience and livelihood security of smallholder rice farming households in Odisha.

DECLARATIONS

Ethics approval and informed consent: Informed consent was obtained from all farmer respondents participating in the study during the course of the research. The study was conducted in accordance with ethical research standards and with the voluntary participation of the respondents.

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Research Article

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Principal Component Analysis of Entrepreneurial Attitude among CUTM Agriculture Students, Odisha

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HIGHLIGHTS

- Agriculture students showed favourable attitude towards entrepreneurship and self-employment.
- PCA extracted five major dimensions of entrepreneurial attitude i.e. Entrepreneurial Management Orientation, Production and Resource Management Orientation, Technical and Monitoring Orientation, Entrepreneurial Career Orientation, and Risk and Marketing Orientation.
- The KMO value (0.808) and significant Bartlett's Test result (χ^2=671, $p < 0.001$) confirmed that the data collected were suitable for PCA.
- Entrepreneurship training is essential for strengthening agripreneurship among students.

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ABSTRACT

The study analysed the entrepreneurial attitude of agriculture students of Centurion University of Technology and Management, Odisha, using Principal Component Analysis (PCA). Data were collected from 83 final-year agriculture students through a pre-tested interview schedule comprising entrepreneurial attitude statements. The reliability of the instrument was assessed using Cronbach's alpha, which yielded a value of 0.861, indicating good internal consistency. The suitability of the data for PCA was examined using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. The KMO value (0.808) and significant Bartlett's Test result (χ^2 = 671, $p < 0.001$) confirmed the adequacy of the dataset for component extraction. PCA with Varimax rotation extracted five major dimensions of entrepreneurial attitude, namely Entrepreneurial Management Orientation, Production and Resource Management Orientation, Technical and Monitoring Orientation, Entrepreneurial Career Orientation, and Risk and Marketing Orientation. The five retained components explained 62.52% of the total variance. The students generally possessed positive attitudes towards self-employment, enterprise management, production efficiency, technical guidance, and market orientation. However, comparatively lower interest in challenging entrepreneurial vocations indicated hesitation towards adopting entrepreneurship as a primary career option. The need for strengthening entrepreneurship-oriented education, experiential learning programmes, start-up incubation support, and market linkage initiatives was felt.

INTRODUCTION

Entrepreneurship is widely recognized as a key driver of economic growth, employment generation, innovation, and rural development. In India, entrepreneurship has gained increasing policy attention due to rising unemployment among educated youth and the need for sustainable livelihood opportunities. Government initiatives such as Startup India, Skill India, and Atmanirbhar Bharat

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have promoted entrepreneurial development by encouraging innovation, skill enhancement, and enterprise creation among young people. Entrepreneurship has also emerged as an effective strategy for improving livelihood security and strengthening rural economies through self-employment and enterprise development (Baishya et al., 2021; Akther, 2023).

In the agricultural sector, entrepreneurship plays a crucial role in addressing challenges such as shrinking landholdings, disguised unemployment, and increasing market competition. Agripreneurship facilitates value addition, agribusiness development, technology adoption, and rural employment generation. Agriculture graduates possess technical knowledge and innovative capabilities that can contribute significantly to the development of successful agricultural enterprises. However, despite expanding opportunities in agribusiness, many agriculture students continue to prefer salaried employment due to perceived risks, financial constraints, uncertainty of returns, and limited entrepreneurial confidence (Banerjee et al., 2020; Sargani et al., 2020; Hou et al., 2026).

Entrepreneurial attitude is considered a critical determinant of entrepreneurial intention and entrepreneurial behaviour. It encompasses an individual's confidence, managerial orientation, risk-bearing ability, innovativeness, and willingness to engage in enterprise creation. Previous studies have reported that entrepreneurial attitude is influenced by entrepreneurship education, family support, institutional environment, leadership ability, and exposure to entrepreneurial training programmes (Gupta et al., 2014; Fragoso et al., 2019; Su et al., 2021; Kusumojanto et al., 2021; Satriadi et al., 2022). Similarly, experiential learning and entrepreneurship-oriented educational interventions have been found effective in strengthening entrepreneurial competencies among agriculture graduates (Lekang et al., 2016; Bochalya et al., 2025).

Entrepreneurial attitude is multidimensional in nature and shaped by behavioural, managerial, technical, and psychological factors (Mei et al., 2020; Cui, 2021; Iqbal et al., 2022). Identifying these underlying dimensions is important for designing targeted entrepreneurship development programmes. Principal Component Analysis (PCA) is a widely used multivariate technique for reducing a large number of interrelated variables into a smaller set of meaningful dimensions and has been successfully applied in entrepreneurship and behavioural studies (Shirur et al., 2019; Mensah & Dadzie, 2020; Ilies et al., 2023).

Although several studies have examined entrepreneurial attitude and entrepreneurial intention among students and entrepreneurs, most have focused on overall attitude levels rather than identifying the underlying dimensions that shape entrepreneurial behaviour. Furthermore, empirical evidence on the dimensional structure of entrepreneurial attitude among agriculture students in Odisha remains limited. Odisha is predominantly an agrarian state where agriculture graduates have significant potential to contribute to agribusiness development, start-up creation, and rural employment generation. Understanding the major dimensions of entrepreneurial attitude among future agricultural professionals is important for developing effective entrepreneurship education and capacity-building interventions. Therefore, the study was undertaken among agriculture students of Centurion University of Technology and Management, Odisha, to identify and analyse the major dimensions of entrepreneurial attitude using Principal Component Analysis and to generate insights for strengthening agripreneurship development among rural youth.

METHODOLOGY

The present study was conducted in Odisha during the academic year 2024–25 to identify the dimensions of entrepreneurial attitude among agriculture students of Centurion University of Technology and Management using Principal Component Analysis (PCA). An *ex-post facto* research design was adopted, as the variables under study had already occurred and were analysed without any experimental manipulation.

The respondents comprised final-year undergraduate agriculture students enrolled at the university, as they had successfully completed courses on Entrepreneurship Development, Business Communication, and Experiential Learning Programme. Out of a total population of 275 students, 83 respondents (51 females and 32 males), representing approximately 30 per cent of the population, were selected through simple random sampling.

Therefore, an interview schedule consisting of 47 statements covering eight dimensions, namely Entrepreneurial Mindset, Risk Orientation, Planning, Production Management, Marketing Management, Credit and Finance, Achievement Orientation, and Socio-cultural Orientation, was developed through an extensive review of literature and consultation with experts in agricultural extension and entrepreneurship. The draft instrument was pre-tested among 20 agriculture students from a non-sample institution to assess the clarity, relevance, ambiguity, and redundancy of the statements. Based on expert judgement and pre-test feedback, 24 statements were excluded due to duplication, poor clarity, limited relevance, or difficulty in interpretation, resulting in 23 statements for the final survey instrument.

Data were collected through personal interviews using a three-point Likert scale consisting of Agree (3), Undecided (2), and Disagree (1). The internal consistency of the scale was assessed using Cronbach's alpha coefficient, which yielded a value of 0.861, indicating good reliability of the instrument. For interpretation of mean scores, the class interval method was employed, wherein mean scores ranging from 1.00–1.66 were categorized as unfavourable, 1.67–2.33 as moderately favourable, and 2.34–3.00 as favourable entrepreneurial attitude.

The collected data were coded, tabulated, and analysed using Jamovi (Version 2.6.44). Descriptive statistics such as mean and standard deviation were used to summarize the responses. Prior to PCA, the suitability of the dataset for factor analysis was assessed using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The KMO value of 0.808 and a significant Bartlett's Test result ($\chi^2 = 671$, df = 136, $p < 0.001$) confirmed the adequacy of the sample and the suitability of the correlation matrix for component extraction. Although larger sample sizes are generally preferred in factor analytic studies, acceptable factor solutions can be obtained with relatively smaller samples when communalities are adequate and factor loadings are sufficiently high (MacCallum et al., 1999).

Principal Component Analysis with Varimax rotation was performed to identify the underlying dimensions of entrepreneurial

attitude among agriculture students. Components with Eigenvalues greater than one were retained following Kaiser's criterion. The scree plot also supported the retention of five principal components. Statements with factor loadings of 0.50 or above and uniqueness values below 0.60 were retained, whereas statistically unsuitable statements exhibiting weak factor loadings, low communalities, or substantial cross-loadings were excluded from the final solution. Consequently, six statements were removed during PCA and 17 statements were retained for interpretation. The retained statements were grouped into five major dimensions, namely Entrepreneurial Management Orientation, Production and Resource Management Orientation, Technical and Monitoring Orientation, Entrepreneurial Career Orientation, and Risk and Marketing Orientation. The five retained components collectively explained 62.52 per cent of the total variance, indicating satisfactory representation of the entrepreneurial attitude construct among agriculture students.

RESULTS

Descriptive statistics of entrepreneurial attitude statements

The descriptive statistics such as mean and standard deviation for the seventeen statements related to the entrepreneurial attitude of agriculture students are presented in Table 1. The mean scores of the statements ranged from 2.28 to 2.73, indicating generally positive attitudes towards entrepreneurship among the respondents. Among all the statements, "Positive thinking to manage adverse situation" recorded the highest mean score (2.73), followed by "Motto for self-employment" (2.68), "Timely use of required inputs and materials" (2.67), and "Proper management of the enterprise to minimize risk" (2.66).

Similarly, "Timely repayment of instalments" (2.64), "Proper insurance coverage" (2.61), and "Collecting marketing information regularly" (2.61) also recorded comparatively higher mean values. The statements "Ensuring timely availability of production inputs" (2.60) and "Close supervision and monitoring of production activities" (2.58) reflected favourable attitudes towards production management practices.

On the other hand, lower mean scores were observed for "Interest for challenging vocation" (2.28), which may reflect students' preference for employment security and their perception of entrepreneurship as a relatively risky career option. Similarly, "Interest to provide employment to others" (2.40) also recorded a comparatively lower mean score, indicating limited inclination among students towards assuming the responsibilities associated with enterprise expansion and job creation. The standard deviation values indicated moderate variability in the responses of the students across the entrepreneurial attitude statements.

Suitability of data for principal component analysis

The suitability of the data for Principal Component Analysis (PCA) was assessed using the Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The results revealed a KMO value of 0.808, which is well above the recommended threshold of 0.50, indicating that the sample size was adequate and the data were appropriate for factor extraction. Furthermore, Bartlett's Test of Sphericity was found to be highly significant ($\chi^2 = 671$, df = 136, $p < 0.001$), suggesting that the correlation matrix was not an identity matrix and that sufficient intercorrelations existed among the variables. These findings confirm that the dataset satisfied the necessary assumptions for conducting Principal Component Analysis and was therefore suitable for identifying the underlying dimensions of agriculture students' attitudes towards entrepreneurship.

Principal component analysis of entrepreneurial attitude

Principal Component Analysis with Varimax rotation extracted five major components with Eigen values greater than one. The rotated component matrix grouped the seventeen entrepreneurial attitude statements into five meaningful dimensions (Table 1).

Table 1. Descriptive statistics, component loadings, uniqueness and dimensions of entrepreneurial attitude among agriculture students

Dimension	Statement	Mean	SD	Component Loading	Uniqueness
Dimension-1 (Entrepreneurial Management Orientation)	Challenging attitude to overcome the loss	2.58	0.528	0.719	0.368
	Positive thinking to manage adverse situation	2.73	0.445	0.682	0.387
	Motto for self-employment	2.68	0.501	0.671	0.437
	Proper management of the enterprise to minimize risk	2.66	0.493	0.611	0.434
	Proper insurance coverage	2.61	0.522	0.634	0.520
Dimension-2 (Production and Resource Management Orientation)	Timely use of required inputs and materials	2.67	0.490	0.770	0.309
	Ensuring timely availability of production inputs	2.60	0.492	0.686	0.457
	Capacity building of the employee	2.53	0.517	0.678	0.419
Dimension-3 (Technical and Monitoring Orientation)	Close contact with the experts	2.52	0.578	0.775	0.340
	Close supervision and monitoring of production activities	2.58	0.528	0.736	0.363
	Timely repayment of instalments	2.64	0.530	0.642	0.346
Dimension-4 (Entrepreneurial Career Orientation)	Interest for challenging vocation	2.28	0.621	0.785	0.317
	More comfortable in developing own business	2.59	0.586	0.784	0.306
	Interest to provide employment to others	2.40	0.583	0.731	0.380
Dimension-5 (Risk and Marketing Orientation)	Adequate risk bearing ability	2.50	0.534	0.778	0.210
	Collecting marketing information regularly	2.61	0.538	0.641	0.377
	Prior agreement with the input dealers	2.53	0.517	0.624	0.399

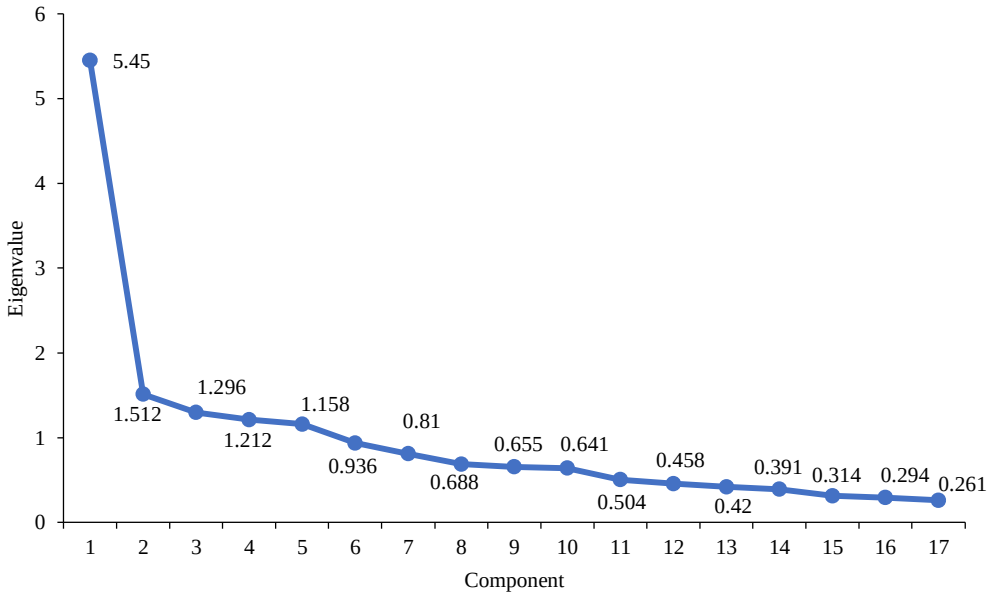


Figure 1. Eigen value of Attitudes of agriculture students towards Entrepreneurship

Eigen value distribution of components

The scree plot presented in Figure 1 indicated that five components possessed Eigen values greater than one. The Eigen values gradually declined after the fifth component, confirming the retention of five principal components for interpretation.

Final Dimensions of entrepreneurial attitude among agriculture students

The results presented in Table 1 reveal the final statements selected for measuring entrepreneurial attitude among agriculture students under five different dimensions and Table 2 depicts the Eigenvalues and Variance Explained by the Retained Components. Principal Component Analysis extracted five components with Eigenvalues greater than one, satisfying Kaiser's criterion for component retention. The first component recorded the highest Eigenvalue (5.45) and explained 32.06 per cent of the total variance. The second, third, fourth, and fifth components had Eigenvalues of 1.512, 1.296, 1.212, and 1.158, accounting for 8.89, 7.63, 7.13, and 6.81 per cent of the total variance, respectively.

The cumulative variance explained by the five retained components was 62.52 per cent, indicating that these components adequately represented the underlying structure of entrepreneurial attitude among agriculture students. The first component contributed the largest proportion of variance, while the remaining four components provided additional explanatory power for understanding the multidimensional nature of entrepreneurial attitude.

These dimensions were named as Entrepreneurial Management Orientation, Production and Resource Management Orientation, Technical and Monitoring Orientation, Entrepreneurial Career Orientation, and Risk and Marketing Orientation.

Under the dimension "Entrepreneurial Management Orientation," five statements were finalized, namely challenging attitude to overcome the loss, positive thinking to manage adverse situations, motto for self-employment, proper management of the enterprise to minimize risk, and proper insurance coverage. These statements indicate the managerial capability, confidence, and preparedness of agriculture students in handling entrepreneurial activities and enterprise-related risks.

The dimension "Production and Resource Management Orientation" included three statements such as timely use of required inputs and materials, ensuring timely availability of production inputs, and capacity building of the employee. These statements mainly focused on efficient utilization of resources, proper planning, and development of manpower for improving enterprise productivity and sustainability.

Similarly, the dimension "Technical and Monitoring Orientation" comprised close contact with the experts, close supervision and monitoring of production activities, and timely repayment of instalments. These statements reflected the importance of technical guidance, monitoring of enterprise activities, and financial discipline among the agriculture students.

The dimension "Entrepreneurial Career Orientation" consisted of interest for challenging vocation, more comfortable in developing own business, and interest to provide employment to others. These statements represented the career aspiration and entrepreneurial motivation of students towards self-employment and enterprise development.

Further, the dimension "Risk and Marketing Orientation" included adequate risk-bearing ability, collecting marketing information regularly, and prior agreement with the input dealers.

Table 2. Eigenvalues and Variance Explained by the Retained Components

Component	Eigenvalue	Variance Explained (%)	Cumulative Variance (%)
1	5.450	32.06	32.06
2	1.512	8.89	40.95
3	1.296	7.63	48.58
4	1.212	7.13	55.71
5	1.158	6.81	62.52

These statements highlighted the importance of market awareness, risk management, and business networking in entrepreneurial success.

DISCUSSION

The findings of the study revealed that agriculture students possessed a moderately favourable entrepreneurial attitude towards self-employment, enterprise management, production planning, technical guidance, and market orientation. The higher mean scores for positive thinking, self-employment orientation, and production management practices indicated that the students had favourable perceptions towards entrepreneurial activities. Similar findings were reported by Saravanan et al. (2025), who found that most final-year agriculture students exhibited a moderately favourable entrepreneurial attitude, while only a small proportion showed a highly favourable attitude.

The Kaiser–Meyer–Olkin (KMO) value of 0.808 indicated adequate sampling adequacy for Principal Component Analysis, as it was substantially higher than the recommended minimum value of 0.50. The obtained KMO value is in line with earlier studies that reported satisfactory PCA outcomes with similar levels of sampling adequacy, thereby confirming the appropriateness of PCA for analysing multidimensional behavioural and socio-economic constructs (Gupta et al., 2020; Yadav et al., 2026). For instance, Shirur et al. (2019) reported a KMO measure of sampling adequacy of 0.819, indicating that the dataset was suitable for variable reduction through Principal Component Analysis. The retention of five components with Eigenvalues greater than one confirms the multidimensional nature of entrepreneurial attitude among agriculture students. The first component alone accounted for 32.06 per cent of the total variance, indicating that entrepreneurial management-related attributes constituted the most influential dimension of entrepreneurial attitude. The substantial contribution of the first component suggests that positive thinking, self-employment orientation, risk management, and enterprise management play a dominant role in shaping entrepreneurial perceptions among students. The cumulative variance explained by the five retained components was 62.52 per cent, which surpassed the commonly accepted threshold for social and behavioural science research. This suggests that the retained components provided a satisfactory representation of the entrepreneurial attitude construct and accounted for a substantial proportion of the variability present in the data (Saha et al., 2026; Shirur et al., 2019). The gradual decline in Eigenvalues indicates that entrepreneurial attitude is shaped by multiple dimensions rather than a single factor. This highlights the need for entrepreneurship development programmes that strengthen managerial, technical, motivational, marketing, and risk-management competencies among agriculture students.

The first extracted component, namely Entrepreneurial Management Orientation, reflected the managerial preparedness and psychological confidence of students towards entrepreneurship. The higher loadings of statements related to risk minimization, positive thinking, and self-employment orientation indicated that students recognized the importance of managerial competency in enterprise success. This finding supports the observations of Nursyirwan et al. (2022), who reported that entrepreneurial attitude and confidence significantly influence entrepreneurial intention among university students.

The second component, Production and Resource Management Orientation, highlighted the importance of timely input management and employee capacity building. Efficient resource utilization and production planning are essential for improving enterprise profitability and sustainability. Similar observations were reported by Stepanenko and Vlasenko (2022), who highlighted the role of supply chain-based inclusive business models in promoting efficient resource management and inclusive agricultural development.

The Technical and Monitoring Orientation component demonstrated that students considered expert guidance, monitoring behaviour, and financial discipline as important entrepreneurial attributes. Regular supervision and technical consultation are important for minimizing enterprise risk and improving productivity. Similar findings were reported by Vijayan et al. (2025), who highlighted the role of experiential learning and technical exposure in enhancing entrepreneurial competencies among agriculture students.

The Entrepreneurial Career Orientation component indicated that students showed preference towards independent business establishment and entrepreneurial professions. However, comparatively lower mean scores for challenging vocation and employment generation suggested hesitation among some students towards adopting entrepreneurship as a full-time career. Fear of risk, uncertainty, and inadequate practical exposure may be possible reasons for this hesitation. Similar findings were reported by Burnette et al. (2020), who found that a growth mindset significantly enhanced entrepreneurial self-efficacy and persistence among university students. This suggests that entrepreneurship education and experiential learning can strengthen students' entrepreneurial confidence and career aspirations.

The Risk and Marketing Orientation component reflected students' awareness of risk-taking ability, market intelligence, and business networking. These factors are critical for enterprise sustainability and profitability in agriculture. The findings are consistent with earlier studies highlighting the importance of market orientation and sound financial decision-making for entrepreneurial success (Ho et al., 2017; Modak et al., 2018; Saghaian et al., 2022).

Overall, the findings indicate that entrepreneurial attitude among agriculture students is multidimensional and shaped by managerial, technical, behavioural, and market-related factors. The results underscore the importance of entrepreneurship-oriented education, experiential learning, start-up incubation support, financial literacy, and market linkage training to promote agripreneurship among rural youth in Odisha. However, the study was confined to final-year agriculture students of a single agricultural institution, which may limit the generalizability of the findings. Future research involving larger and more diverse samples across different universities and regions is recommended to validate the extracted dimensions and strengthen the robustness of the results.

CONCLUSION

The study concluded that agriculture students of Centurion University of Technology and Management possessed a moderately favourable entrepreneurial attitude towards self-employment,

enterprise management, production efficiency, technical guidance, and marketing activities. Principal Component Analysis successfully reduced the entrepreneurial attitude statements into five major dimensions, namely Entrepreneurial Management Orientation, Production and Resource Management Orientation, Technical and Monitoring Orientation, Entrepreneurial Career Orientation, and Risk and Marketing Orientation. The findings indicated that entrepreneurial attitude among agriculture students is multidimensional and influenced by managerial, technical, behavioural, and market-related factors. However, comparatively lower interest towards challenging entrepreneurial vocations suggests the need for strengthening entrepreneurship-oriented education, experiential learning, startup incubation support, and financial literacy programmes to promote agripreneurship and rural employment generation among youth in Odisha.

DECLARATIONS

Ethical approval and consent to participate: Our study did not require ethical approval. However, the informed consent obtained from all respondents before data collection.

Consent of publication: Participants provided consent for publication.

Competing interests/author contributions: No competing interests were declared. Conceptualization and designing of research (RKB); Field survey and data collection (RKB, AK, CP); Analysis of data and interpretation (RKB, AK, CP); Preparation of manuscript (RKB, AK, CP).

Conflict of interest: No conflicts of interest among the authors. The authors declare that during the preparation of this work, thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

Software used: Principal Component Analysis (PCA) was performed using *jamovi* version 2.6 (The jamovi project, 2024), which operates on the *R* statistical computing environment version 4.4 (R Core Team, 2024). Additional psychometric analyses were conducted using the *psych* package (Revelle, 2023).

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Research Article

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Predicting Artificial Intelligence Awareness among Agricultural Professionals Using Random Forest and SHAP Analysis

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HIGHLIGHTS

- Awareness of artificial intelligence among agricultural professionals increased significantly with greater acquaintance and exposure to AI tools and positively influenced by the implementation of AI.
- Participation in seminars and training sessions improved awareness and knowledge of AI.
- Digital information and mass media exposure helped raise knowledge of AI technologies.

ARTICLE INFO

Keywords: Artificial intelligence, Awareness, Agricultural professionals, Random forest, SHAP analysis.

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ABSTRACT

Agriculture plays an important role in economic development, rural livelihoods and food security. The increasing integration of artificial intelligence (AI) technologies in agriculture has enhanced productivity, decision-making and resource management. The present study was conducted during 2024-2025 among agricultural professionals working under Acharya N. G. Ranga Agricultural University (ANGRAU) in Andhra Pradesh to assess their awareness of AI and identify the factors influencing it. Correlation analysis, Random Forest regression, Permutation Feature Importance (PFI), SHAP analysis (SHapley Additive exPlanations), Partial Dependence Plots (PDP), Individual Conditional Expectation (ICE) and interaction analysis were employed for data analysis. The findings revealed that agricultural professionals possessed a moderately high level of AI awareness. Technical exposure-related factors, particularly familiarity with AI tools, practical application of AI technologies, participation in seminars and training programmes, and media exposure, emerged as the most influential predictors of AI awareness. The interpretability analyses further demonstrated that technology-oriented variables contributed more strongly to awareness levels than demographic characteristics. The study highlights the importance of strengthening capacity-building initiatives, experiential learning opportunities and digital extension programmes to enhance AI readiness among agricultural professionals and support the effective integration of AI-based innovations in agricultural extension systems.

INTRODUCTION

Availability of food, livelihoods of farmers and economic growth can be affected by agriculture in many countries (Eli-Chukwu, 2019). The need for sustainable food production systems will increase as the global population will cross the mark of 10 billion by the year 2050. Therefore, there is a need to improve existing agricultural systems. Agriculture continues to play a crucial role in livelihoods and food security across developing countries

(Rose et al., 2021). Various technologies are gradually introduced in agriculture to solve those problems (Ruzzante et al., 2021; Niranjan et al., 2023). ICT-enabled extension systems have emerged as important tools for improving farmers' timely advisory services (Singh & Mathur, 2024; Sebastian & Jeyalakshmi, 2019).

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Artificial intelligence refers to those computational systems that are used to perform tasks which would normally require the reasoning ability and judgment of humans. Some of the AI technologies which have been introduced include machine learning, computer vision, robotics, predictive analytics and Internet of Things (IoT) technologies (Naik et al., 2025).

AI technologies not only make real-time data analysis possible but can also enhance decision-making on the farm through efficient methods. AI systems assist farmers to take important decisions, increase production and decrease wastage of resources (Liu, & Wang, 2021; Barman et al., 2026). The use of computer vision aids in pest and disease diagnosis, and the use of robotic systems ensures labor-independent operations and increased efficiency (Liakos et al., 2018). Also, AI-based advisory systems and digital extension platforms facilitate provision of information to farmers (Kumar et al., 2025).

Andhra Pradesh is one of India's agriculturally progressive states, with increasing emphasis on digital agriculture, precision farming and technology-enabled extension services. Agricultural professionals working under Acharya N. G. Ranga Agricultural University (ANGRAU) were chosen as respondents because they play a pivotal role in agricultural research, education and extension activities.

The application of AI systems in agriculture in India is still low due to various reasons like lack of awareness, lack of technical skills, low digital literacy, infrastructural barriers and high cost of implementation (Satapathy et al., 2024a; Chandra et al., 2024). Agricultural professionals play a key role in disseminating new technologies and guiding farmers. Awareness and understanding of AI technologies among agricultural professionals greatly influence the adoption and implementation of digital agriculture practices (Talaviya et al., 2020). Previous studies have indicated that awareness, training, digital exposure and access to information sources significantly influence technology adoption behaviour (Singh et al., 2023; Khanganbi & Priya, 2024). Although several studies have examined AI applications in agriculture and factors influencing technology adoption, empirical evidence on AI awareness among agricultural professionals remains limited (Panda et al., 2017; Patil et al., 2018; Devi, 2020; Shehrawat et al., 2024). Furthermore, studies employing interpretable machine learning techniques such as Random Forest, SHAP analysis, PDP and ICE to identify the determinants of AI awareness are scarce, particularly in the context of Andhra Pradesh. This knowledge gap restricts the development of targeted capacity-building strategies for agricultural extension personnel. Therefore, the present study entitled "Predicting Artificial Intelligence Awareness among Agricultural Professionals Using Random Forest and SHAP Analysis" was undertaken to assess the awareness level.

METHODOLOGY

In order to examine the variables impacting agricultural professionals' awareness of artificial intelligence (AI) in Andhra Pradesh in 2024-2025, the study used a correlational research approach. Because of its strong participation in agricultural education, research and extension initiatives throughout the state, Acharya N.G. Ranga Agricultural University (ANGRAU) was purposefully chosen as the study's location. The study's respondents were agricultural professionals employed by Krishi Vigyan Kendras (KVKs), Colleges and Regional Agricultural Research Stations (RARS) and Research stations. These institutions were purposively selected because they are actively engaged in agricultural research, technology assessment, extension education and farmer advisory services. The total population consisted of approximately 350-400 agricultural professionals working in ANGRAU-affiliated institutions. From this, a purposive sample of 120 respondents was selected based on their involvement in ICT-based agricultural activities. The objectives of the study, as well as related research findings regarding AI, machine learning and agriculture extension studies, were used while preparing the schedule. The interview schedule was pre-tested with 30 agricultural professionals who were not included in the final sample. AI awareness procedure and schedule developed by Vikas (2022) was followed for the study. The responses were obtained on three-point continuum scale as fully aware, aware and not aware against each statement and weightage was given as 3, 2 and 1, respectively.

Machine learning techniques were employed for this data analysis. Predictive analysis involved splitting the data into 80% training data and 20% testing data because of its capacity to model non-linear relationships between predictor variables, Random Forest regression algorithm was selected. The model was initially configured using 400 decision trees as a default parameter to ensure stability. However, hyperparameter tuning using Out-of-Bag (OOB) validation showed that 200 trees produced the optimal performance (highest OOB $R^2 = 0.668$). Therefore, 200 trees were selected as the final optimal configuration for interpretation and reporting. Since a constant level of predictions was required, the algorithm used had 400 decision trees, bootstrapping and out-of-bag validation techniques. Performance of the model was evaluated using the coefficient of determination (R^2) and out-of-bag (OOB) validation statistics. A Pearson correlation matrix was computed among all predictor variables and the dependent variable (AI awareness). Predictive variables that contribute to AI awareness were identified by permutation feature importance. SHAP analysis (SHapley Additive exPlanations), Partial Dependence Plot (PDP) and Individual Conditional Expectation (ICE) were utilized to interpret the contribution and behaviour of predictors.

RESULTS

Out-of-Bag (OOB) R^2 versus number of trees in the random forest

The OOB validation results indicated that the predictive performance of the Random Forest model improved as the number of trees increased. The model achieved its highest OOB R^2 value at 200 trees, after which only minor fluctuations in performance were observed. This pattern suggested that the model reached stability at 200 trees and that increasing the number of estimators beyond this level did not result in meaningful improvements in predictive accuracy. Therefore, 200 trees were considered optimal for subsequent analyses (Figure 1). However, it was found that there was a small decline in the model performance after 200 trees as OOB R^2 values for 300, 400 and 600 trees were 0.6610, 0.6529

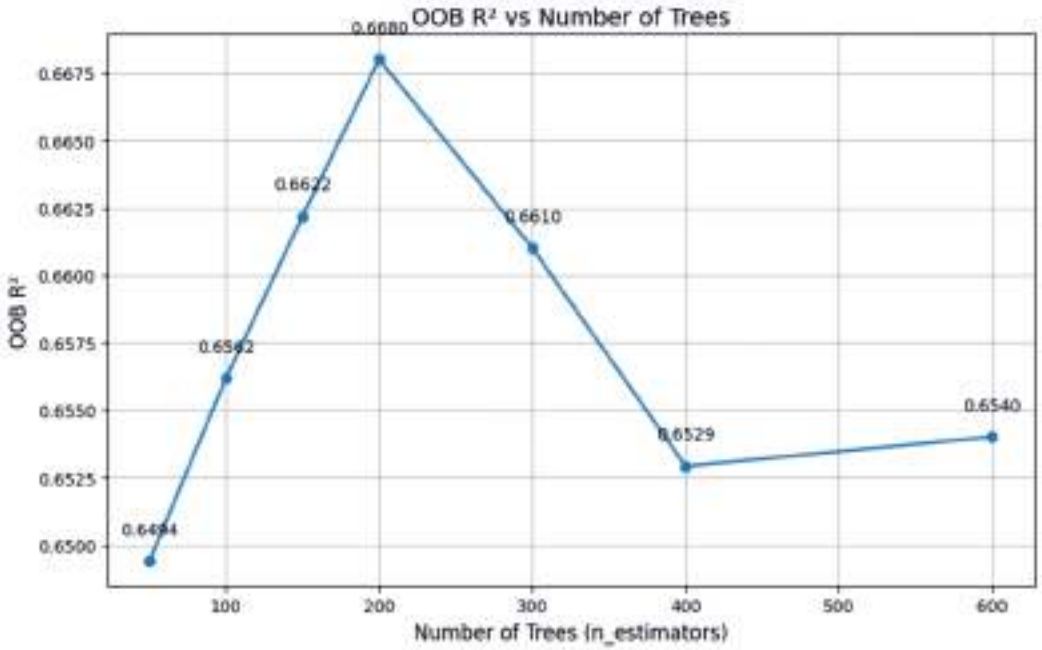


Figure 1. Out-of-Bag (OOB) R^2 versus Number of Trees in the Random Forest

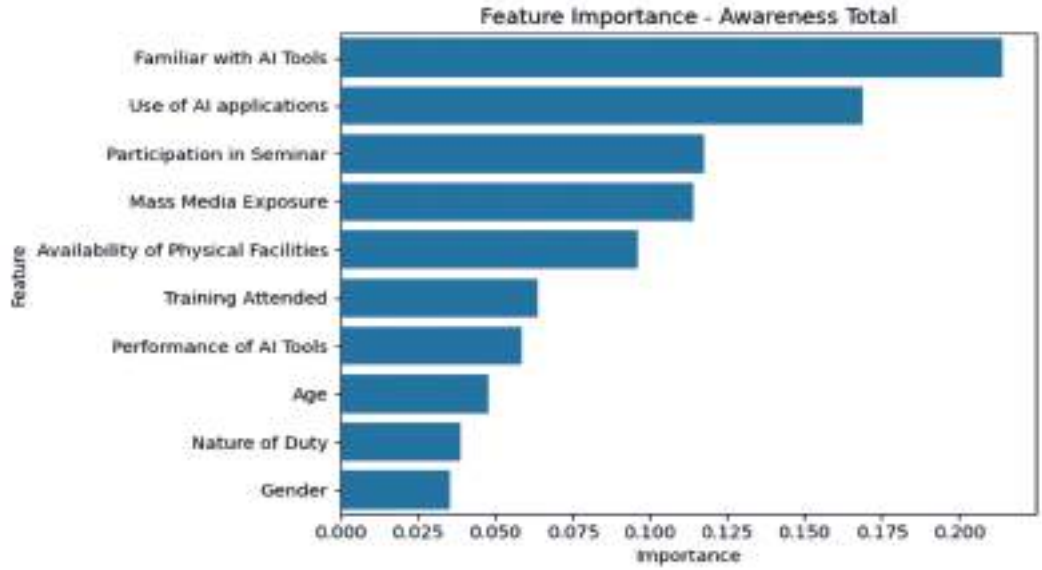


Figure 2. Permutation feature importance on the training set

and 0.6540, respectively. As the number of trees increased in building the model, the OOB R2 values also increased.

Permutation feature importance on the training set

The permutation feature importance analysis revealed that AI-related exposure variables contributed more substantially to awareness prediction than demographic variables (Figure 2). Familiarity with AI tools and the use of AI applications emerged as the most influential predictors, followed by participation in seminars and media exposure. These findings suggested that practical engagement with AI technologies played a greater role in determining awareness levels than personal characteristics. The predictor variable having the highest significance level (0.215) is the use of AI tools, followed by the use of AI applications (0.168). The predictor variables that rank second in importance are attendance at seminars (0.118) and media exposure (0.114).

The moderate contributions came from training attendance (0.064), performance of AI tool (0.059) and availability of physical facilities (0.096). The importance values of Age (0.048), Nature of Duty (0.039) and Gender (0.035) were relatively lower. Familiarity with AI technologies was found to have significantly more contribution to the awareness prediction as compared to demographics. Also, there was a significant decline in the value of important features. Results showed that exposure to technology was more influential in increasing AI awareness compared to demographic characteristics. Technical familiarity, application of the AI tool, participation in training sessions, and information exposure became increasingly important for awareness enhancement regarding AI. In comparison with technology variables, demographic characteristics were relatively less influential in predicting awareness.

SHAP Summary plot for Random Forest Model

The SHAP summary analysis (SHapley Additive exPlanations), demonstrated that technology-related variables exerted the strongest influence on awareness predictions (Figure 3). Familiarity with AI tools and the use of AI applications consistently contributed positively to awareness levels, whereas demographic variables exhibited relatively limited influence. The distribution of SHAP values indicated that technical exposure and engagement with AI-related activities were the primary drivers of awareness among agricultural professionals. Given the SHAP values ranging from -12.0 to +18.0, the variable contributing the most was the familiarity with artificial intelligence tools. The AI application was the second-largest contributor, where its SHAP value ranged between -8.0 and +7.0. Predicted awareness scores were affected by higher usage of artificial intelligence applications. Attending seminars and the media, on the other hand, in addition to having a SHAP value range of -8.0 and +4.0, played a relatively positive role. As for the prediction of awareness, low exposure scores contributed negatively, whereas high exposure scores contributed positively. Training attendance and AI performance had moderately varying SHAP values, which were about -4.0 and +4.0. Physical availability had quite limited variation near zero.

Demographic attributes such as Gender, Nature of Duty, Experience, Age and Education are some of the demographic attributes analyzed whose SHAP values were fairly concentrated around the zero-axis indicating their insignificance to the model predictions. While Age possessed some negative outliers reaching down to -8.0, Education was the least dispersed attribute indicating that it was insignificant to knowledge predictions. Through the SHAP distribution chart, it became clear that training experience, seminars attended, technical skills and AI utilization were far much significant factors influencing AI knowledge acquisition compared to any other demographic attribute. This was through the colour scheme used to display SHAP values on the chart (Ghosh et al., 2025).

Partial Dependence Plot (PDP) and Individual Conditional Expectation (ICE) analysis

The PDP and ICE analyses revealed that higher levels of familiarity with AI tools and greater use of AI applications is associated with increased awareness levels. The relatively consistent ICE curves around the PDP trends indicated that these effects were observed across most respondents. Media exposure also contributed to awareness, although its influence was comparatively less pronounced than that of AI familiarity and application use. The individual plots with ICE overlays provided useful representations of marginal responses from the Random Forest model. It can be observed in Figure 4a (Familiarity with AI Tools), the average PDP graph was relatively stable at the lower familiarity levels and remained almost constant from level 1 to 3. The higher familiarity levels led to an abrupt increase in the average PDP plot, reaching its peak at level 4. At this level, there was a remarkable growth in predicted awareness scores up to almost 185. This trend was consistent for agricultural experts as reflected in the proximity of ICE graphs with the average PDP.

Average PDP Graph for Mass Media Exposure (Figure 5a) depicted a relatively low response trend. In all ranges considered, the expected awareness values gradually declined from close to 168 to 155. Since they had better access to information sources and digital education facilities, those participants who had a greater

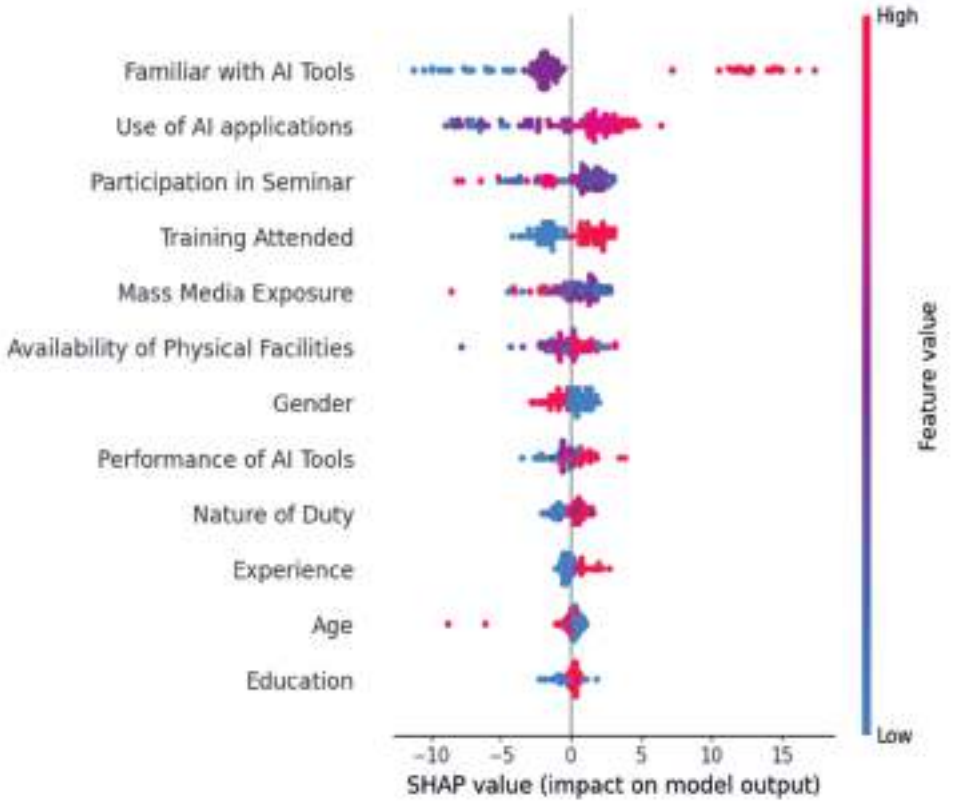


Figure 3. SHAP Summary Plot for Random Forest Model

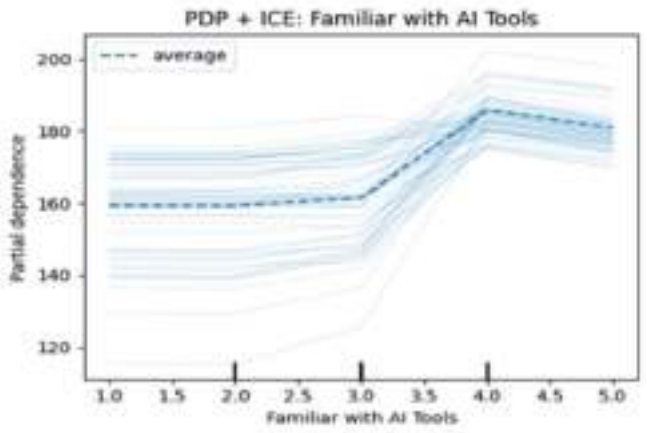


Figure 4a. Partial dependence with individual conditional expectation plot for Familiarity with AI tools

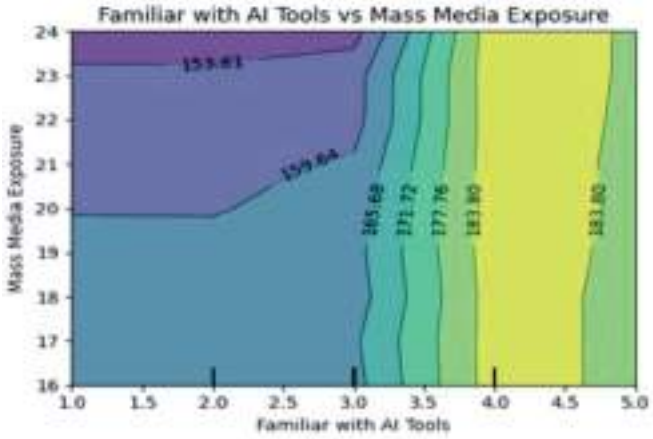


Figure 4b. Two-dimensional partial dependence of AI Awareness: Familiarity with AI Tools × mass media exposure

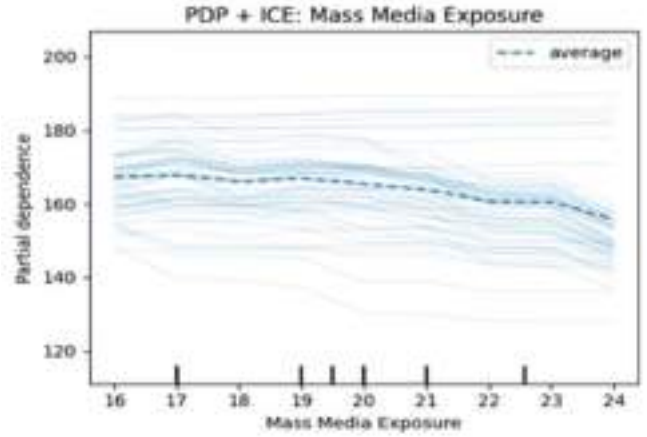


Figure 5a. Partial dependence with individual conditional expectation plot for mass media exposure

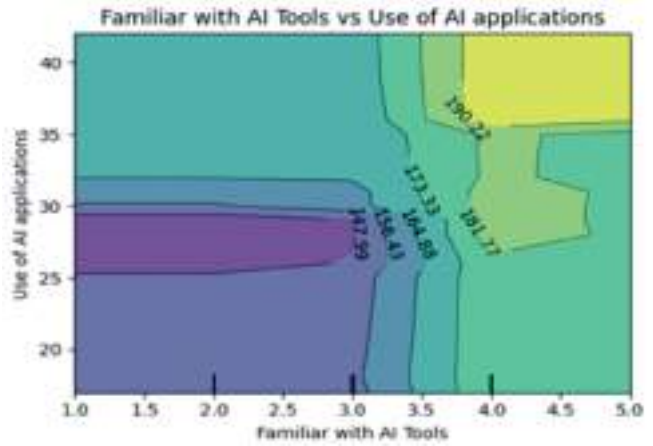


Figure 5b. Two-dimensional partial dependence of AI Awareness: Familiarity with AI Tools × Use of AI applications

degree of media exposure were able to keep their awareness levels comparatively high despite having relatively lesser variability compared to AI tool familiarity and AI application usage. The ICE profiles revealed relatively little variability against the average graph.

At lower levels of AI application utilization, Figure 6a (Use of AI Applications) demonstrated a very consistent average partial dependency. But after level 29, when the expected awareness values became close to 175, the curve showed a sharp positive increase. The ICE lines showed comparatively parallel upward movement around the PDP curve, indicating that respondents' awareness prediction was consistently positively impacted by the use of AI applications. The pattern showed that agricultural expert's awareness of AI technology was greatly enhanced by their practical use of AI applications similar finding with Saha et al. (2024).

Interaction effects among predictor variables

The interaction analyses demonstrated that awareness levels increased when agricultural professionals simultaneously possessed greater familiarity with AI technologies, higher usage of AI applications and stronger media exposure. Among the interactions examined, familiarity with AI tools combined with AI application usage produced the strongest positive effect on awareness prediction. These findings highlighted the complementary role of technical exposure and information access in enhancing AI awareness.

In Figure 4b (Mass Media Exposure x Familiar with AI Technologies), it can be observed that, irrespective of the level of media exposure, the projected values of awareness increased considerably with increasing familiarity with AI technologies. The least prediction value observed was approximately 153.61 and the maximum prediction value was observed in greater levels of familiarity, specifically in the intervals between levels 4 and 5, where the prediction value for awareness was about 183.80. The graph shown in Figure 5b (Familiarity with AI Tools × Usage of AI Applications) clearly showed that there was much better awareness prediction with increased familiarity with AI tools and increased use of AI applications. The best interaction area was the one where the highest level of predictive accuracy was observed and the predicted value of awareness was around 190.22. Low levels of predictive performance were attributed to low levels of familiarity with AI tools and low usage of AI applications. The fact that the lines formed a sloped contour indicates an additive effect on the prediction of awareness.

According to Figure 6b (Mass Media Exposure × Use of AI Applications), it was clear that with an increase in the levels of

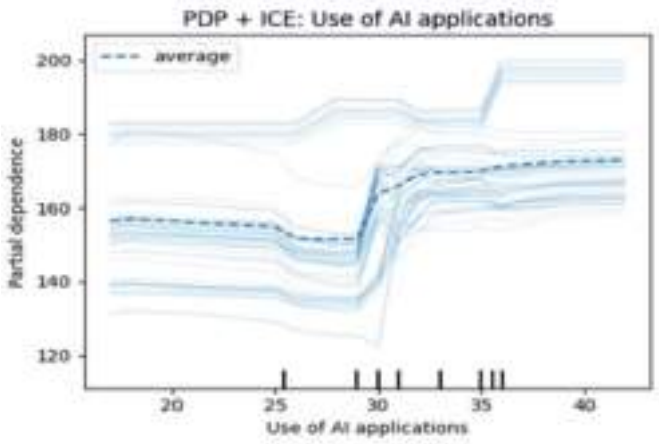


Figure 6a. Partial dependence with individual conditional expectation plot for use of AI applications

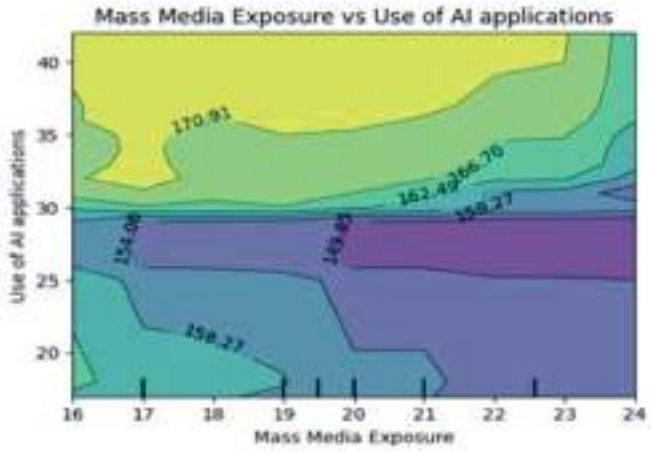


Figure 6b. Two-dimensional partial dependence of AI Awareness: Mass media exposure × Use of AI applications

both variables, the predictive values steadily increased. The high levels of both media exposure and use of AI applications led to a maximum predictive value which was almost equal to 170.91. Even though the combination of both variables contributed to a significant increase in predictive values, the interaction plane had smaller magnitude values for low levels of both media exposure and use of AI applications. The isoclines seemed to be slightly diagonal which implied that changes in both factors could equally contribute to increasing awareness.

DISCUSSION

The findings demonstrated that awareness of artificial intelligence among agricultural professionals was influenced primarily by their exposure to AI-related knowledge, applications and learning opportunities rather than by demographic characteristics. This suggests that awareness is a dynamic attribute that can be enhanced through institutional interventions, training and practical engagement with digital technologies. The ability of the Random Forest model to effectively predict awareness levels further indicates that the selected variables captured important dimensions of AI readiness among agricultural professionals (Sahoo et al., 2025). These findings support the growing recognition that technology adoption in agriculture depends not only on access to innovations but also on the knowledge ecosystem surrounding potential users (Ryo, 2022; Sondarava et al., 2023).

The prominence of AI familiarity, application of AI technologies, seminar participation and media exposure indicated that experiential learning and continuous professional development play a critical role in enhancing awareness among the professionals. These findings are consistent with the observations of Satapathy et al. (2024b), who reported that access to information and technological exposure significantly influenced digital technology adoption. However, the present study extends previous research by demonstrating, through interpretable machine learning techniques, the relative importance of these factors in predicting AI awareness. Similarly, the positive contribution of seminars and mass media exposure supports the findings of Suman et al. (2025), who highlighted the role of information dissemination channels in strengthening technology awareness among extension personnel specially in agriculture field. Unlike conventional studies that relied primarily on descriptive or regression approaches, the present study provides deeper insights into the interaction and relative contribution of awareness determinants through SHAP (SHapley Additive exPlanations) and interaction analyses.

The findings have important implications for agricultural field, extension education and policy. Since technical exposure and practical engagement with AI emerged as key determinants of awareness, extension organizations and university should design structured capacity-building programmes that combine theoretical understanding with hands-on training and experience learning of AI applications in agriculture and allied field. Regular training programmes, workshops, demonstration activities and digital learning platforms may help agricultural professionals develop confidence in utilizing AI-based tools, apps and advisory systems. Furthermore, strengthening digital literacy and promoting access to reliable information sources can facilitate wider acceptance of AI technologies within extension systems. At the policy level, institutions and university may consider integrating AI competency development into professional training curricula and agricultural extension service frameworks to support the transition towards data-driven and technology-enabled agricultural advisory services system. Despite its contributions, the study has certain limitations. The findings were based on agricultural professionals associated with ANGRAU in Andhra Pradesh and therefore may not be fully generalizable to professionals working in other states or institutional settings. The use of purposive sampling may also limit broader representation of the agricultural professional population. In addition, the study assessed awareness at a single point in time and did not capture changes in awareness resulting from future technological developments or training interventions. Future research may employ longitudinal designs, larger and more diverse samples and comparative studies across regions to obtain a more comprehensive understanding of AI awareness and adoption among agricultural professionals.

CONCLUSION

The study demonstrates that awareness of artificial intelligence among agricultural professionals is influenced primarily by technical exposure, familiarity with AI tools, practical application of AI technologies, participation in seminars and access to information sources. The findings indicate that technology-related factors contribute more strongly to AI awareness than demographic characteristics. These results highlight the importance of strengthening professional competencies and digital readiness to support the effective integration of AI into agricultural extension systems. To enhance AI awareness, agricultural institutions should organize regular hands-on training programmes, AI-focused workshops and experiential learning activities. Incorporating AI modules into professional development curricula and expanding access to digital information platforms can further improve awareness and adoption. Institutional support for continuous capacity building and technology-oriented extension services is essential for developing an AI-ready agricultural workforce capable of promoting digital agriculture innovations.

DECLARATIONS

Ethics approval and informed consent: Throughout the study, the respondents were asked for their informed consent.

Conflict of interest: The research was carried out without any financial or commercial ties that might be seen as a potential conflict of interest, according to the authors. The authors affirm that they carefully examined, amended and edited the content as necessary when preparing this work. The final content of this publication is entirely the authors' responsibility.

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Research Article

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Comparative Analysis of Entrepreneurial Behaviour among Pokkali and Non-Pokkali Farmers in Kerala

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HIGHLIGHTS

- Pokkali farmers had a significantly higher level of entrepreneurial behaviour compared to non-pokkali farmers
- Extension contact and information sources were positively associated with entrepreneurial behaviour among Pokkali farmers.
- This valuable traditional system faces severe challenges, causing rapid decline and emphasizing the urgent need for immediate, targeted interventions.

ARTICLE INFO

Keywords: Entrepreneurial behaviour, Agriculture, Pokkali cultivation, Kerala.

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ABSTRACT

In Kerala's coastal districts of Ernakulam, Alappuzha, and Thrissur near the Arabian Sea, Pokkali rice farming is a long-standing, organic, traditional, and environmentally beneficial style of paddy production. The study was conducted in 2025 to compare the entrepreneurial behaviour between Pokkali and non-Pokkali farmers. A pre-tested interview schedule was used to gather primary data from 120 respondents and focus groups with key informants were conducted to validate the results. The Cronbach's alpha value obtained was 0.826 for the 31-item scale. The results revealed that Pokkali farmers exhibited significantly higher entrepreneurial behaviour compared to non-Pokkali farmers. Among Pokkali farmers, extension contact, source of information and social participation exhibited a positive and significant relationship with entrepreneurial behaviour. Despite its ecological and economic importance, Pokkali cultivation has declined considerably in recent years due to multiple constraints. Therefore, strengthening such traditional and integrated farming systems through targeted extension interventions, capacity building, institutional support, and conservation efforts may support the development of entrepreneurial competencies, improve livelihood security, and contribute to sustainable agricultural development.

INTRODUCTION

Rice (*Oryza sativa*) is the most important staple cereal, sustaining nearly two-thirds of the world's population. The livelihood of a large section of humanity depends on rice due to its high nutritive value and energy content (Burlando & Cornara, 2014). According to the Food and Agriculture Organization (FAO), global rice production during 2024–25 was estimated at 546.6 million tonnes, with India as the leading producer followed by China. In Kerala, paddy has traditionally been a major food crop; however, the area under cultivation has declined drastically over time. From 8.82 lakh hectares in 1974–75, to 1.66 lakh hectares by 2019–20 (Sabu & Roy, 2024). In 2024–25, rice accounted for only 7.01 per cent of the total cropped area, with 1.76 lakh hectares under cultivation, producing 5.30 lakh tonnes with a productivity of 3,006 kg per hectare. The area under wetland paddy further declined marginally by 1.45 per cent, while production remained nearly constant (Kerala Economic Review, 2025).

The decline in paddy cultivation is attributed to factors such as land conversion, low profitability, inadequate institutional

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support, rising labour wages, price fluctuations, fragmented holdings, and unscientific cultivation practices (Rejula et al., 2017; Jayaprada et al., 2023). This has resulted in a widening gap between demand and production, highlighting the need to revive sustainable and traditional farming systems. In the context of growing emphasis on organic agriculture, indigenous systems like Pokkali rice cultivation offer significant potential, particularly in stress-prone coastal ecosystems (Sudan et al., 2016).

Pokkali rice cultivation is a unique, eco-friendly farming system practiced in the saline tracts of Kerala. It involves cultivating salt-tolerant rice during the monsoon, followed by prawn farming in the same fields, forming a sustainable agri-aqua integration (Sreelatha et al., 2022a). The system depends on natural tidal flows and monsoonal patterns, establishing a symbiotic relationship between rice and aquatic organisms (Ranjith et al., 2018). In Kerala, where a considerable portion of paddy lands remain waterlogged, such integrated systems are common (Jayan & Sathyanathan, 2010). The traditional practice of prawn filtration (*Chemmeen Kettu*) enhances farm income and system efficiency. Pokkali cultivation is environmentally sustainable as it minimizes external inputs, conserves biodiversity, and avoids degradation of natural resources (Jose et al., 2023a). It is recognized as a model of sustainable agriculture integrating crop and aquaculture systems (Sumithra & Devi, 2025a).

Despite its advantages, Pokkali cultivation faces several challenges, including labour shortages, socio-economic constraints, and environmental pressures, leading to a sharp decline in area from 25,000 hectares to less than 5,000 hectares (Vikas et al., 2018). Scarcity of labour, particularly during harvesting, has been identified as a major constraint (Jose et al., 2023b). Given these challenges, there is a need to understand the role of such systems in shaping farmers' behaviour. Previous studies on Pokkali cultivation have predominantly focused on ecological sustainability, integrated rice-prawn production systems, economic benefits, and production constraints. However, limited empirical research has examined the entrepreneurial behaviour of farmers engaged in Pokkali cultivation. Entrepreneurial behaviour plays a crucial role in innovation adoption, risk management, market orientation, and enterprise development. Given the unique agro-ecological and management characteristics of the Pokkali farming system, differences in entrepreneurial behaviour may exist between Pokkali and non-Pokkali farmers. Therefore, the present study was undertaken to compare the entrepreneurial behaviour of Pokkali and non-Pokkali farmers in Kerala.

METHODOLOGY

The current study was conducted in the year 2025 in the state of Kerala. The study adopted an ex-post facto comparative research design to examine the differences in the entrepreneurial behaviour between Pokkali and non-Pokkali farmers. Since the variables under study had already occurred naturally and could not be manipulated experimentally, an ex-post facto approach was considered appropriate. Kerala has 16 districts out of which pokkali cultivation is practiced only in 3 districts, namely Ernakulam, Alappuzha and Thrissur. More than half (64.00%) of the total pokkali cultivation is practiced in the district of Ernakulam (Sumithra & Devi, 2025b), therefore Ernakulam district was purposively selected for the present study. There are 14 RD blocks in Ernakulam district. Out of these blocks, North Paravur, Aluva and Kalamassery are popularly practicing pokkali cultivation and Mulanthuruthy with non-pokalli rice cultivation (Kerala Economic Review, Volume 2, 2025) blocks were purposively selected for the study. From the selected RD blocks, one village each from the three selected pokalli rice cultivated RD blocks were selected purposively for this study as per the availability of pokkali rice cultivators and three villages from non-pokkali cultivated RD block were selected randomly, to get a total of 6 villages for the present study. A total of 120 respondents was selected purposively for this study whereby 20 respondents were selected purposively from each pokkali paddy cultivated villages and 20 respondents each from non-pokkali paddy cultivated villages, thus, making it a total of 120. Data were collected through personal interviews using a structured and pre-tested interview schedule. Descriptive statistics such as frequency, percentage, mean and standard deviation along with chi-square test, correlation analysis and independent samples t-test were carried out using SPSS Version 16.0.

Chi-square test of independence was employed to examine the association between farmer type (Pokkali and non-Pokkali) and selected socio-economic characteristics of the respondents. The test was used to determine whether significant associations existed between the two groups with respect to variables such as age, education, landholding, area under cultivation, annual income, farming experience, extension contact, training exposure, social participation, and source of information.

The components of entrepreneurial viz. innovativeness, risk orientation, scientific orientation and marketing orientation were adopted with slight modifications (Bushetti & Krishnamurty, 2022). Necessary modifications were incorporated to improve clarity, relevance, and suitability of the statements. The schedule was pre-tested among non-sample respondents to ensure comprehensibility and applicability under field conditions. Reliability of the entrepreneurial behaviour scale was assessed using Cronbach's alpha coefficient. Each component was represented by a different number of statements with distinct scoring ranges. The statements were measured on five-point continuum ranging from strongly agree, agree, undecided, disagree and strongly disagree with weightage of 5, 4, 3, 2 and 1 respectively and was reversed in case of negative statements. The weighted responses of each statement were added up to determine the respondents' overall score for each component.

Pearson's correlation analysis was carried out to examine the association between entrepreneurial behaviour and socio-economic characteristics of the respondents. The analysis helped in identifying the degree and direction of association between the dependent and independent variables. Entrepreneurial behaviour among farmers is influenced by various socio-economic and psychological factors. Variables such as education, farming experience, landholding, annual income, and social participation are often associated with decision-making ability, access to information, risk-bearing capacity, innovation adoption, and market orientation. Farmers with better educational exposure and resource availability are generally more capable of adopting innovative practices and responding to market opportunities. Therefore, selected socio-economic variables were

examined to understand their relationship with entrepreneurial behaviour among Pokkali and non-Pokkali farmers.

Independent samples t-test was used to compare the entrepreneurial behaviour of Pokkali and non-Pokkali farmers and to determine whether significant differences existed between the two groups. Preliminary analyses were conducted to assess the assumptions of the independent samples t-test. The Shapiro–Wilk test indicated a slight deviation from normality among Pokkali farmers ($W = 0.946$, $p = 0.011$), whereas the distribution among non-Pokkali farmers was normal ($W = 0.983$, $p = 0.558$). Given the sample size of 60 respondents in each group, the t-test was considered sufficiently robust. Levene's test indicated unequal variances between the groups ($F = 27.861$, $p < 0.001$); therefore, the results corresponding to the "equal variances not assumed" condition were interpreted.

RESULTS

Association between farmer type and socio-economic characteristics

The association between farmer type and selected socio-economic characteristics was assessed using Chi-square test. The results revealed that educational status, land holding, area under cultivation, extension contact, and training exposure showed significant association with farmer type. However, age, annual income, farming experience, social participation, and source of information did not differ significantly between Pokkali and non-Pokkali farmers, indicating comparability of the groups with respect to these characteristics. Since significant differences were observed in selected socio-economic characteristics between the two groups, the findings were interpreted with due consideration of potential confounding effects.

Table 1. Association between farmer type and socio-economic characteristics

Variables	χ^2 value	p-value
Age	1.046	0.593
Education	13.488	0.036*
Land holding	29.408	<0.001**
Area under cultivation	37.059	<0.001***
Annual income	0.057	0.972
Farming experience	0.500	0.779
Extension contact	32.528	<0.001**
Training exposure	84.324	<0.001**
Social participation	0.569	0.752
Source of Information	1.118	0.572

*Significant at 5 per cent level (p<0.05); **Significant at 1 per cent level (p<0.01)

Reliability statistics of entrepreneurial behaviour scale

Reliability analysis of the entrepreneurial behaviour scale was carried out using Cronbach's alpha coefficient to assess the internal consistency of the instrument. The Cronbach's alpha value obtained was 0.826 for the 31-item scale, indicating good reliability and satisfactory internal consistency of the instrument used in the study.

Table 2. Reliability statistics of entrepreneurial behaviour scale

Particulars	Value
Cronbach's Alpha	0.826
Number of items	31

Relationship between entrepreneurial behaviour and socio-economic variables

Correlation analysis was carried out to examine the relationship between entrepreneurial behaviour and selected socio-economic characteristics of Pokkali and Non-Pokkali farmers. The results of the correlation coefficients indicating the significant relationships between entrepreneurial behaviour and the selected characteristics of the respondents are presented in Table 3.

Among Pokkali farmers, extension contact ($r = 0.576$) and source of information ($r = 0.387$) exhibited a positive and highly significant relationship with entrepreneurial behaviour, while social participation ($r = 0.263$) showed a positive and significant relationship. The findings indicate that greater interaction with extension agencies, better access to information sources and higher social participation were positively associated with entrepreneurial behaviour among Pokkali farmers.

In contrast, none of the selected socio-economic variables showed a significant relationship with entrepreneurial behaviour among non-Pokkali farmers.

Table 3. Relationship between entrepreneurial behaviour and socio-economic variables

Variables	Pokkali	Non-Pokkali
Age	0.026	0.042
Education	-0.115	-0.105
Land holding	0.193	0.083
Area under cultivation	0.161	0.120
Annual income	0.045	-0.217
Farming experience	-0.038	0.191
Extension contact	0.576**	-0.163
Training exposure	0.101	0.028
Social participation	0.263*	-0.033
Source of Information	0.387**	0.087

*Significant at 5 per cent level; **Significant at 1 per cent level

Note: No significant relationship was observed among non-Pokkali farmers.

Comparison of entrepreneurial behaviour between Pokkali and non-Pokkali farmers

The independent samples t-test revealed a highly significant difference in entrepreneurial behaviour between Pokkali and non-Pokkali farmers, t (84.34) = 53.165, $p < 0.001$. Pokkali farmers recorded significantly higher entrepreneurial behaviour scores (221.02 ± 11.32) than non-Pokkali farmers (134.98 ± 5.38). The mean difference was 86.03 points (95% CI: 82.82–89.25), with an extremely large effect size (Cohen's $d = 9.74$).

DISCUSSION

The findings revealed significant differences between Pokkali and non-Pokkali farmers with respect to several socio-economic and

Table 4. Comparison of entrepreneurial behaviour between Pokkali and non-Pokkali farmers

Variable	Pokkali (Mean ± SD)	Non-Pokkali (Mean ± SD)	*t*-value	df	*p*-value	95% CI	Cohen's *d*
Entrepreneurial behaviour	221.02 ± 11.32	134.98 ± 5.38	53.165	84.34	<0.001**	82.82 – 89.25	9.74

entrepreneurial characteristics. The Chi-square analysis indicates that educational status, land holding, area under cultivation, extension contact and training exposure are significantly associated with farmer type, whereas age, annual income, farming experience, social participation and source of information do not differ significantly between the groups. Similar observations are reported in studies where education, landholding and extension-related variables are positively associated with entrepreneurial behaviour among farming communities (Patil et al., 2017; Sharma et al., 2019). The significant association of training exposure with farmer type highlights the importance of capacity-building programmes in fostering entrepreneurial behaviour. Entrepreneurship-oriented training enhances knowledge, skills and confidence required for enterprise development. Similar findings were reported by Sharma and Singh (2023), who observed substantial improvement in entrepreneurial competencies following entrepreneurship training programmes, and by Kumari et al. (2025), who emphasized the role of agribusiness training in strengthening entrepreneurial capabilities among agripreneurs. Kobba et al. (2021) observed in the farm sector, four determinants of entrepreneurial success were family size, land size, turnover and annual income whereas in the non-farm sectors five determinants of entrepreneurial success were long term involvement, initiative, number of employees, entrepreneurial experience and annual income. Kademani et al. (2026) reported that operational elements such as training institute-industry market-entrepreneur linkages, administrative commitments, and policy consistency, collectively shaped intervention effectiveness across the entrepreneurial ecosystems.

The reliability analysis demonstrates that the entrepreneurial behaviour scale possesses good internal consistency, as indicated by the Cronbach's alpha value of 0.826. This confirms that the modified instrument reliably measures entrepreneurial behaviour and provides consistency in assessing the entrepreneurial characteristics of the respondents.

The correlation analysis reveals a clear trend among Pokkali farmers. Extension contact exhibits a positive and highly significant relationship with entrepreneurial behaviour, followed by source of information and social participation (Pisure et al., 2014). These findings indicate that farmers who maintain regular interaction with extension agencies, actively participate in social organizations and access multiple information sources tend to display stronger entrepreneurial behaviour (Pongener & Jha, 2024). Extension systems facilitate knowledge acquisition, exposure to innovations and improved decision-making, thereby strengthening entrepreneurial competencies (Kapadnis & Thoke, 2024; Gudla et al., 2026).

An important exception emerges among non-Pokkali farmers, where none of the selected socio-economic variables show a significant relationship with entrepreneurial behaviour. This suggests that entrepreneurial behaviour within this group may be influenced by factors beyond the variables included in the present investigation. Psychological attributes, market opportunities, risk perception, enterprise diversification and local institutional support may play a greater role in determining entrepreneurial orientation among non-Pokkali farmers. The absence of significant relationships also indicates that conventional socio-economic variables alone may not adequately explain entrepreneurial behaviour in all farming contexts. Diversified systems provide exposure to multiple income sources and management practices, thereby facilitating the development of entrepreneurial competencies (Nain et al., 2019; Sreelatha et al., 2022b). Farmers engaged in diversified farming systems tend to exhibit higher entrepreneurial orientation and adaptability (Shahbaz et al., 2023; Rizzo et al., 2023; Wang et al., 2023; Thakur et al., 2025). In contrast, non-Pokkali farmers largely depend on monocropping systems, which may restrict opportunities for innovation and market engagement.

The independent samples t-test further reveals a highly significant difference between the two groups with respect to entrepreneurial behaviour. Pokkali farmers record substantially higher entrepreneurial behaviour scores than non-Pokkali farmers. This finding suggests that the specialized nature of Pokkali cultivation is associated with greater innovativeness, management ability, market orientation and decision-making capacity. Pokkali farming is characterized by unique agro-ecological conditions and often requires continuous adaptation, technical guidance and institutional interaction, which may strengthen entrepreneurial attributes among farmers. This finding is in agreement with Mukharjee and Ghosh (2025), who reported that institutional support, knowledge access and enterprise-related exposure positively influence entrepreneurial behaviour among agricultural entrepreneurs.

Overall, the findings indicate that entrepreneurial behaviour is more strongly shaped by informational and institutional factors than by basic demographic characteristics. The results emphasize the importance of strengthening extension contact, training programmes and information dissemination mechanisms to enhance entrepreneurial behaviour among farming communities, particularly among non-Pokkali farmers who appear to benefit less from these support systems.

CONCLUSION

Entrepreneurial behaviour among Pokkali farmers exhibited a positive and significant relationship with extension contact, social participation and access to information sources, highlighting the importance of institutional and informational support in fostering entrepreneurial competencies. Significant differences were also observed between the two groups with respect to education, landholding, area under cultivation, extension contact and training exposure. The entrepreneurial behaviour is associated with extension services, capacity-building programmes and access to

information. Enhancing training opportunities, extension outreach and information dissemination mechanisms may support the development of entrepreneurial behaviour among farming communities.

DECLARATIONS

Ethics approval and informed consent: Throughout the study, the respondents were asked for their informed consent.

Conflict of interest: The research was carried out without any financial or commercial ties that might be seen as a potential conflict of interest, according to the authors. The authors affirm that they carefully examined, amended and edited the content as necessary when preparing this work. The final content of this publication is entirely the authors' responsibility.

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Research Article

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Factors Influencing Farmers' Perception of Climate Variability and Change in Kano State, Nigeria

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HIGHLIGHTS

- Socio-economic factors such as age, education, farming experience and household income were significantly affecting farmers' perception of climate change and variability.
- Inconsistent information sources negatively affect perception quality.
- Improved access to education and reliable extension contacts is essential for better perception of climate change.

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ABSTRACT

The study examined the socio-economic determinant of farmers' perception of climate change in Kano State, Nigeria in 2025. A quantitative research design was employed using structured questionnaires received from 369 farmers with minimum of 10 years' experience. Descriptive statistics, composite perception index and multiple linear analysis were used for analysis of data. The level of perception index indicate a high level of climate change awareness among farmers (Mean =3.11), while rainfall unpredictability, temperature changes and declining agricultural productivity being the most perceived indicators. Multiple regression analysis showed that annual household income, farming experience, age, and education positively and significantly influenced farmers' perception of climate change (R^2 = .636, $p < 0.05$). Contrarily, source of information had significant and negative effect, highlighting that increase access to information does not necessarily means better understanding because of issues around quality and reliability. The study concludes that while farmers perceived climate change, their understanding level is driven by socio-economic variables and reliable sources of information. The study recommends focus on improving access to education, enhancing extension services and ensuring dissemination of reliable climate information to strengthen farmers' ability to respond to climate change.

INTRODUCTION

Agriculture is an important sector ensuring food supplies, raw materials for agro-based industries, greater employment opportunities and sustainable livelihoods. However, the sector is increasingly confronted with climate change, which refers to long time shifts in weather patterns and temperature caused mostly by human activities (United Nations, n.d.). Climate change continues to threaten agricultural and food production worldwide. Global food security and livelihood sources are being disrupted by unpredictable weathers, rising temperature and extreme weather events. The reliance of agriculture on weather and natural resources exposes it more to climate shocks (Sthitaprajna & Shasani, 2026). Recent studies indicate that climate change is becoming more pronounced globally, placing agricultural productivity and livelihoods at high risk (Intergovernmental Panel on Climate change [IPCC], 2021). Due to its heavy reliance on rainfall, low technology and investments,

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agriculture is in developing countries is expected to experience severe impacts (IPCC, 2022).

Agriculture in many African countries is highly vulnerable to climate change because farming systems are predominantly rainfed and constrained by limited access to inputs, insurance, and capital. Over 60% of rural households in sub-Saharan Africa depend on agriculture for food and livelihoods (Shuaibu & Nchak, 2021). Climate variability, including rising temperatures, irregular rainfall, droughts, floods, and increased pest and disease outbreaks, has adversely affected agricultural productivity and sustainability, threatening the livelihoods of smallholder farmers (Ezeh et al., 2026). If current trends persist, crop yields in sub-Saharan Africa are projected to decline by 10–40% by 2050 (IPCC, 2018).

Nigeria, the populous African country has an estimated population of about 241 million people (Worldmeters, 2026). It relies heavily on agriculture for employment (about 70%) and rural livelihoods making it highly vulnerable to climatic shocks (Central Bank of Nigeria [CBN], 2024). Climate change is expected to deteriorate food security, while increasing pressure on resources; water, arable lands, and livestock feed (Braun et al., 2023). Despite these challenges, agriculture must continue to meet the growing food and nutritional demands of population.

There are many empirical studies on farmers' perception of climate change. However, these studies are diverse and shaped by socio-economic characteristics. Socio-economic factors considered key variables influencing perceptions to climate change (Kumar & Saxena, 2024). More educated farmers or household with reliable information are more likely to perceived climate change and make creative decisions (Ghanghas et al., 2015; Ahmed & Givens, 2025). Despite growing research in Nigeria, there is limited empirical data focusing specifically on socio-economic determinants of farmers' perception of climate change especially at rural levels where most agricultural production take place.

In line of this, the research aims to bridge the void by assessing the determinants of farmers' perceptions of climate change in Kano state Nigeria. Notably, it investigates how selected socio-economic characteristics influence perceptions of climate change. The results are expected to contribute to the existing literature and provide empirical evidence for improved agricultural production and sustainable livelihoods.

METHODOLOGY

The study was conducted in 2025 in Bichi Local Government Area (LGA), Kano State, Nigeria. Situated within the Sudan Savannah agro-ecological zone, the area is predominantly agrarian, with a rainy season extending from May to October. Major crops include rice, maize, groundnut, millet, guinea corn, vegetables, and Bambara nut. Bichi was selected due to its vulnerability to climate change and reliance on rain-fed agriculture.

A descriptive correlational research design was used. The target population comprised 75,000 registered farmers. Based on the Krejcie and Morgan (1970) table, 382 respondents were selected, with 369 valid responses analyzed. A multi-stage sampling procedure was employed: Bichi LGA was purposively selected for its agricultural importance, and respondents were randomly chosen from 11 wards with proportional village representation. Only farmers with a minimum of 10 years' farming experience were included in the study.

Variables were coded as follows: age (≤20 years (1), to >50 years (5), education (no education (0) to vocational training (5), farming experience (10 years (1) to ≥41 years (5), source of information (media (1), extension officer (2), fellow farmers (3), local leaders (4) NGOs (5), others (6), and annual household income (low (1), medium (2), high (3). Binary variables were measured on a two-point scale Yes (2), No (1); using the midpoint of 1.50, mean scores ≥1.50 indicated accepted sources, while scores <1.50 indicated non-accepted sources.

Data were collected using a validated questionnaire. Farmers' perceptions of climate change were measured on a 4-point Likert scale (1 = Strongly Disagree to 4 = Strongly Agree). The instrument yielded a Cronbach's alpha of 0.71. A composite perception index (1.00–4.00) was computed by averaging item scores and categorized using the equal interval method (Omorogiuwa, 2018) as low (1.00–1.99), moderate (2.00–2.99), or high (3.00–4.00).

Descriptive statistics and multiple linear regression were used to analyze the data at the 5% significance level using SPSS:

$$Y_i = \beta_0 + \beta_1 (\text{Age}) + \beta_2 (\text{Education}) + \beta_3 (\text{Farming experience}) + \beta_4 (\text{Source of information}) + \beta_5 (\text{Annual household income}) + \varepsilon i$$

Where, Y_i is the perception score, β_0 is the intercept, β_1–β_5 are regression coefficients, and εi is the error term.

RESULTS

Farmers' perception of climate change indicators

The level of perception index presented in Table 1 shows that farmers in the study area had a high perception of climate change indicators, with the overall mean of 3.11. Rainfall unpredictability had the highest mean score (Mean = 3.409), followed by temperature change (Mean = 3.358). Agricultural productivity decline (Mean = 3.218), pest and disease incidence (Mean = 3.163), flood and erosion related events (Mean = 3.163), and drought and water scarcity (Mean = 3.098) were highly perceived by the farmers. However, perceived change in rainfall amount (Mean = 2.832) and storm and wind intensity (Mean = 2.832) recorded moderate perception levels.

Farmers access to climate change information

Data descriptive statistics data disclosed that farmers relied on multiple sources of information pertaining climate change. Extension workers emerge as the most important source of information with 82.66 %, fellow farmers is next with 63.14% and media with (56.64 %). The cumulative mean score (1.549) is above the decision threshold (1.50), indicating acceptable level of information access. Meanwhile, reliance on information from informal source such as fellow farmers and leaders may sometimes be misleading or lack reliability and accuracy as my may affect quality of the information (Table 2).

Socio-economic determinant of farmers' perception

The data summary of multiple regression show that farmers' perceptions of climate change are strongly associated with their

Table 1. Level of perception of climate change indicators among farmers

Climate indicator	Mean score	Standard Deviation	Interpretation
Temperature change	3.358	0.672	High perception
Perceived change in rainfall amount	2.832	0.713	Moderate perception
Pest and disease incidence	3.163	0.671	High perception
Storm and wind intensity	2.832	0.713	Moderate perception
Flood and erosion	3.163	0.800	High perception
Drought and water scarcity	3.098	0.543	High perception
Agricultural Productivity decline	3.218	0.412	High perception
Rainfall unpredictability	3.409	0.880	High perception
Overall Perception Index	3.11		High perception

Note: Perception levels were classified using the equal interval method: 1.00 – 1.99 = Low; 2.00 - 2.99 = Moderate, 3.00 – 4.00 = High. (*Source:* Omorogiuwa, 2018).

Table 2. Source of climate change information among the farmers

S.No.	Source of Information	Yes (Freq.)	Yes (%)	No (Freq.)	No (%)	Mean	Std. Dev.
1	Media	209	56.64	160	43.36	1.566	0.701
2	Extension Officers	305	82.66	64	17.34	1.827	0.511
3	Fellow Farmers	233	63.14	136	36.86	1.631	0.379
4	Local Leaders	148	40.10	221	59.89	1.401	0.577
5	NGOs	198	53.66	171	46.34	1.537	0.811
6	Others	123	33.33	246	66.67	1.333	0.489
	Cumulative Mean					1.549	

Note: Division Rule ≥1.50 = Accepted source

socio-economic characteristics. The coefficient determination (R^2 = .636) suggest that approximately 63.60% of the variation in the perceptions is explain by the model. This indicates a good model fit and highlights the variables relevance. Durbin- Watson value (2.018) show lack of autocorrelation and confirm model reliability estimates (Table 3).

Regression coefficient analysis was employed to obtain the contribution of individual variable; age was positive and significantly affect perception ($\beta = 0.170$, $p < 0.05$), indicating aged farmers may likely perceived changes in climate better. This may be due to their prolonged involvement in farming and years of experience in tracking environmental changes.

Education also indicate a positive and statistically significant relationship ($\beta = 0.096$, $p < 0.05$), showing that more educated farmers are likely to have a better understanding of climate change because of the expected improve information processing ability.

Farming experience was found to be positive ($\beta = 0.266$, $p < 0.05$), highlighting the role of experience in improving perception. Farmers with more years' experience tend to identify climate trends and impacts.

Annual household income happens to had the significant positive influence ($\beta = 0.387$, $p < 0.05$), demonstrating that wealthy households are positioned to had better access to information, resources and technologies which enhance their perception of climate change. Contrary to this, source of information showed a negative influence but significant relationship ($\beta = -0.203$, $p < 0.05$). This finding suggests possible limitations in the relevance, quality or reliability of the information sources available. The result indicates increased access to information does not always mean better understanding or perception especially when it is from unreliable and inconsistent sources (Table 4).

Regression equation

The estimated regression equation for predicting farmers' perception of climate change is:

$$Y = 10.033 + 0.722X_1 + 0.369X_2 + 0.958X_3 - 0.596X_4 + 2.499X_5$$

Where, Y = Perception of climate change, X_1 = Age, X_2 = Education, X_3 = Farming experience, X_4 = Source of Information, X_5 = Annual household income.

DISCUSSION

The level of perception of climate change indicators reveals high perception of climate change among farmers. This suggests that farmers in the study have substantial awareness of climate-related changes, which may be attributed to prolonged farming activities and exposure to environmental changes. Highly favourable

Table 3. Summary of multiple regression of socio-economic determinants of farmers' perception of climate change

Model	R	R^2	Adjusted R^2	Std. Error	F Change	df1	df2	Sig.	Durbin- Watson
1	0.798	.636	0.631	3.027	127.054	5	363	0.000	2.018

Note: Predictors: Age, Education, Farming Experience, Source of Information, Annual Income
Dependent Variable: Perception of Climate Change

Table 4. Estimated regression coefficients

Variable	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
Constant	10.033	0.700		14.322	0.000		
Age	0.722	0.155	0.170	4.649	0.000	0.751	1.331
Education	0.369	0.130	0.096	2.825	0.000	0.870	1.149
Farming Experience	0.958	0.147	0.266	6.533	0.000	0.604	1.656
Information Sources	-0.596	0.100	-0.203	-5.984	0.000	0.870	1.149
Annual Income	2.499	0.253	0.387	9.879	0.000	0.652	1.533

Note: Dependent Variable: Perception of Climate change.

perception of rainfall unpredictability and changes in temperature indicates that farmers are concerned about climatic factors that directly influence planting decisions, agricultural yields and productivity. These findings are consistent with those of Yeleliere et al. (2023). However, farmers in the present study perceived rainfall unpredictability more strongly, likely due to their prolonged exposure to local climate trends. This suggests regional differences in how farmers perceive and rank climate indicators.

The strong perception of pests and diseases incidence and declining agricultural productivity reflects the practical experience of the respondents, as these factors have direct economic implications. This supports the argument that farmers' perception is mainly centred on observable climate impacts. Similarly the moderate perception of storm intensity and rainfall variability suggest that they occur less frequently in the study area.

The regression results indicate that socio-economic characteristics play a crucial role in influencing farmers' perception of climate change. The selected variables explained 63.6% of the variation in climate perception (R^2 = .636). The significant influence of age on perception of climate change suggests that older farmers are more likely to recognize changes in climatic conditions than younger farmers. This may be attributed to their longer period of interaction with the farming environment, which provides an extensive experience and basis for comparing past and present climatic patterns. This finding contrasts with Okafor et al. (2024), who reported that older farmers are generally less likely to adopt technology-based climate adaptation strategies. However, this may be due to the distinction between perception and adaptation. While adaptation often requires innovation, investment and willingness to accept new practices, perception depends on the ability to observe and interpret environmental changes. Similarly, Olugbenga et al. (2025) reported that younger farmers were more innovative, productive and more likely to engage with climate information. However, the present study highlights that greater innovation does not necessarily equate to stronger climate perception, rather, accrued environmental experience seems to play a more important role in shaping farmers' recognition of climate changes.

The positive influence of income indicates that economic resources may enhance farmers' capacity to access climate information, training opportunities and adaptive technologies. This finding is consistent with Olugbenga et al. (2025), who reported that farmers with higher incomes were better positioned to invest in agricultural inputs and respond to climate-related risks. Although, their study focused on investment decisions under climate variability, both studies indicate that financial capacity influences how farmers engage with climate-related challenges. Farmers with greater economic resources may have more opportunities to obtain information and assess environmental changes, which strengthens their perception of climate change. Omokpariola et al. (2025) reported similar findings that poor households are less likely to mitigate climate impacts due to poor access to resources (money, credits) and their subsistence nature increases their vulnerability and limit their resilience.

The significant influence of farming experience and age highlights the value of accumulated environmental knowledge in shaping climate perception. This suggests that perception is not always driven by formal knowledge, but also by accumulated practical experience and observations. Although, Sthitaprajna and Shasani (2026), reported young farmers tend to be more adaptable to climate change related challenges, their finding focused on adaptation practices rather than perception of climate change. Moreover, both findings suggest that farming experience improves farmers' ability to understand and respond to climatic challenges. The consistency the two studies positioned practical experience as an important asset in building climate awareness and resilience. Mishra et al. (2025) also observed that older farmers are more likely to adopt climate mitigation measures more effectively than younger farmers in Odisha, India. This complements finding by suggesting that age and experience not only enhances perception but also strengthens adaptation.

The positive influence of education aligns with the existing literature, stressing that literacy improves access to available information and strengthen decision-making ability. Moreover, the low level of tertiary education suggests the need for improved training, inclusion of climate change in to school curricula and enhance extension services. This agrees with the study by Babu et al. (2025) who reported that education improves mitigation capacity of farmers through increasing access to information, improving perceptions, and knowledge and guide farmers in making productive decisions. While their study focused on mitigation capacity, the present study shows that education also strengthens perception particularly where tertiary education is limited.

The negative relationship between information sources and climate perception suggest that the quality and credibility of information may be more important than the quantity of information received by the farmers. This finding contradicts Sthitaprajna and Shasani (2026), who reported that information-source utilization contributes positively to farmers' adaptive capacity. However, their study also observed a negative regression coefficient for information source utilization, where the authors attributed this to possible deficiencies in the quality of available information. The similarity in direction between the two studies

suggests that access to information alone may not guarantee improved climate understanding. When information is informal, inconsistent and poorly communicated, increased exposure may lead to confusion rather than improve perception. This reiterates the need for an improved extension system that will ensure timely dissemination of reliable and consistent climate information. This interpretation is further supported by Arunachalan et al. (2025) and Madaki et al. (2023), who reported that regular extension contact improves farmers' access to information, adoption of better agricultural practices, productivity, income and climate change awareness.

The regression results are reinforced by the composite perception result, which shows a higher level of climate change awareness among the respondents. The significant influence of selected socio-economic variables such as income, farming experience and education helps explain the observed variation in perception levels of various climate indicators. This entails that while farmers recognise climate change, the magnitude and accuracy of their perception are shaped by their socio-economic characteristics (Shitu & Nain, 2025), which links the perception with the determinants identified in regression model.

Generally, the findings underscore the importance of direct interaction with the environment in influencing climate change perception and reiterate the need for improved and sustainable extension services in the region aimed at improving the dissemination of reliable knowledge of climate change and variability for enhanced perception and resilient agricultural production.

CONCLUSION

The study reveals that farmers in the study area possess high level of awareness of climate change. However, the extent of this perception is significantly shaped by socio-economic factors. Income, age, farming experience and education positively influence perception, with income being the strongest determinant. The negative effects of sources of information indicate that access alone is insufficient unless the information is consistent, and reliable. Therefore, extension agencies should fortify the dissemination of validated climate information to the farmers through regular farmer training and advisory services. Efforts should focus on improving farmers' access to financial support and educational opportunities to strengthen their capacity to access climate information and employ appropriate adaptation measures. Similarly, integrating climate change education into extension programmes and adult learning can enhance farmers' understanding and decision making abilities. These measures would help strengthen the resilience of agricultural livelihoods and improve informed adaptation response in the study area.

DECLARATIONS

Ethics approval and informed consent: Throughout the study, the respondents were asked for their informed consent.

Conflict of interest: The research was carried out without any financial or commercial ties that might be seen as a potential conflict of interest, according to the authors. The authors affirm that they carefully examined, amended and edited the content as necessary when preparing this work. The final content of this publication is entirely the authors' responsibility.

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Research Article

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Digital Technology Use for Agricultural Extension Information among Rural Leaders in Tel Kayf District

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HIGHLIGHTS

- Rural leaders showed favourable use of digital technology for agricultural information.
- Age, education and information sources were the major predictors of digital technology use.
- High mobile phone prices and Internet costs were the major constraints to digital use.

ARTICLE INFO

Keywords: Digital technology, ICT adoption, Internet access, Iraq, Mobile phone use, Nineveh.

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ABSTRACT

Digital technology has become increasingly important as an extension support tool, facilitating access to current agricultural information. The current research evaluated the utilisation of digital technology by rural leaders to obtain agricultural information in Tel Kayf District, Nineveh Governorate, Iraq. A multi-stage sampling method was applied and 101 rural leaders were selected from three villages. The data were collected in June 2024 via face-to-face interviews employing a structured questionnaire. The use of digital technology was evaluated using 20 statements on a five-point rating scale. Mean, standard deviation, relative importance, frequency, percentage and random forest regression were applied for the analysis. The findings showed mean item scores exceeded 4.0 on a five-point scale across all twenty statements. The random forest regression model achieved a test R^2 of 0.3920 in the utilisation of digital technology. Age was the most influential variable, followed by education and information sources. The high prices of modern mobile phones and Internet charges were the main barriers. The findings imply that the existing favourable use of digital technology among rural leaders can be leveraged through affordable Internet access, practical skill enhancement and locally relevant digital extension content to strengthen agricultural information dissemination in rural communities.

INTRODUCTION

Technology is an integral part of modern societies, affecting the generation, storage, retrieval and utilisation of information across various industries, including agriculture. Technology plays a crucial role in human development. However, its latest manifestation, namely digital technology, provides greater opportunities for communication, learning and decision-making (Ram et al., 2020). This shift is essential within the context of agriculture since the industry has direct impacts on food security, economic stability and development (Karikari et al., 2015). The development of agriculture relies not only on tangible resources and technological advances but also on rural populations' ability to access and utilise relevant information. The increasing use of digital technology in rural marketing and agriculture illustrates its potential to facilitate more efficient communication and enhance information transfer

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between institutions and farmers (Rushchitskaya et al., 2024). In this respect, agricultural extension is critical in linking research and technology with farmers through advice and behaviour modification (Olalekan, 2024; Shitu et al., 2025; Barman et al., 2026).

With rapid technological changes, there is a need for an extension system that can deliver relevant, location-based agricultural information. Digital means like mobile phones, Internet access, search engines and online advice websites play a significant role in reducing the distance between farmers, extension workers and scientific organisations (Yu et al., 2024). Additionally, rural leadership is key because leaders often play a role in decision-making and information dissemination in agriculture (Wilmot, 2024). Digital technology is therefore considered an important instrument for improving the functioning and sustainability of agricultural extension services. It reduces spatial and temporal barriers and opens wider communication channels for serving farming communities (Liu et al., 2023). However, the effective use of such technologies depends on users' access, education, skills, and confidence (Dibbern et al., 2024). The emergence of computers, the Internet, and mobile phones necessitates strengthening digital capacity among rural users and agricultural stakeholders (Amran et al., 2024).

In Iraq, recent attention to rural knowledge, environmental crisis management and agricultural information systems highlights the need to understand how rural communities respond to modern information sources (Al-Daudee & Masso, 2025). Educational institutions also have an important role in preparing competent agricultural human resources capable of using modern information systems for rural development (Cárdenas Alonso & Nieto Masot, 2022). However, evidence on the use of digital technology for agricultural information by rural leaders in Nineveh Governorate remains limited. Therefore, the present study is undertaken to assess the use of digital technology, such as mobile phones, internet access, search engines, agricultural websites, social media, digital communication tools, and computer-based agricultural calculations, used to obtain, process, or share agricultural information by rural leaders in the Tel Kayf District of Nineveh Governorate. Rural leaders often act as informal extension agents, opinion leaders, information brokers, peer educators and diffusion agents in rural communities. The study also examines the contributions of age, education, origin, information sources and training to digital technology use and identifies the major constraints limiting effective use of digital tools.

METHODOLOGY

The study was conducted in selected villages of Tel Kayf District, Nineveh Governorate, Iraq. The research population consisted of farmers from five villages in the Alqosh area. A multi-stage sampling procedure was followed. First, three villages were randomly selected from the five, resulting in an accessible population of 270 farmers. Second, potential rural agricultural leaders were identified in consultation with village-level key informants and local agricultural personnel. Rural agricultural leaders were defined as active farmers locally recognised for their ability to access, interpret and share agricultural information. Identification criteria included active involvement in farming, regular interaction with other farmers, use of multiple information sources and participation in communicating agricultural information within the local farming community. From these, 101 rural agricultural leaders were selected for interview, representing 37.4% of the accessible farmer population.

Primary data were collected in June 2024 through personal interviews using a structured questionnaire. The questionnaire had two sections: the first covered age, education, origin, sources of agricultural information and participation in digital technology training; the second measured the use of digital technology to obtain agricultural information. Initially, 25 statements were prepared after reviewing literature and consulting subject specialists. After expert screening, 20 statements were retained for final data collection. Digital technology usage was assessed using a 20-item, five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Content validity was established through expert review by 20 experts from the Universities of Mosul and Dohuk. Items with at least 80% agreement were retained. A pilot study (n=20) yielded a Cronbach's alpha of 0.85, indicating acceptable internal consistency.

Data analysis was done through mean, standard deviation, rank, relative weight, frequency and percentages. The digital technology use score was predicted through a random forest regression model. The random forest technique is preferred due to its ability to accommodate non-linear interaction and relationships among predictors (Breiman, 2001). Model performance was evaluated using the coefficient of determination (R^2), mean absolute error (MAE) and root mean square error (RMSE). Feature importance and Shapley Additive Explanations (SHAP) values were used to interpret the models (Lundberg & Lee, 2017).

RESULTS

Digital technology adoption among rural leaders

According to Table 1, rural leaders extensively used digital technology to access agricultural information. The mean values for all 20 statements ranged from 4.00 to 4.49, indicating a positive trend toward the adoption of digital technologies in agricultural activities. The weights were also relatively high, ranging from 0.800 to 0.897, suggesting that digital technology was a significant source of agricultural information for respondents.

"The digital technology enables me to access current information at an agricultural level," obtained the first rank with a mean score of 4.49 and a relative weight of 0.897. "The Internet allows me to access agricultural information," ranked second with a mean score of 4.47 and a relative weight of 0.893. "I remain updated on the global happenings using digital technology," occupied the third position with a mean score of 4.43 and a relative weight of 0.885. Based on the above findings, it can be concluded that respondents used digital devices to access current agricultural information.

Those statements about the usefulness of the technology at the farm level also received high rankings. "The use of digital technology makes it easy for me to do my agriculture practice" was fourth on the list with an average score of 4.41. "The Internet makes most of the things needed for agricultural practice available" was fifth with an average score of 4.39. The ease of agricultural activities due to mobile phone use ranked sixth, with an average score of 4.38.

Table 1. Use of digital technology by rural leaders for agricultural information

Rank	Statement	Mean	Standard Deviation	Relative Weight
1	Digital technology helps me obtain up-to-date information at the agricultural level.	4.49	0.57	0.898
2	The Internet helps me get timely agricultural information.	4.47	0.69	0.894
3	I keep pace with developments in the world through my use of digital technology.	4.43	0.67	0.886
4	Digital technology helps me practice my agricultural work more easily.	4.41	0.61	0.882
5	The Internet contributes to obtaining most of the resources I need in my agricultural work.	4.39	0.84	0.878
6	Using a mobile phone helps make agricultural operations easier.	4.38	0.84	0.876
7	Digital technology helps me gain up-to-date information about agriculture.	4.35	0.78	0.870
8	Digital technology reduces the effort expended in some work.	4.34	0.84	0.868
9	My use of digital technology helps me develop my learning abilities.	4.26	0.80	0.852
10	Ease of calling and getting help while using a mobile phone.	4.25	0.89	0.850
11	Most digital technology helps me obtain up-to-date information in agriculture.	4.22	0.87	0.844
12	I prefer to use the Google search engine to obtain agricultural information.	4.21	0.83	0.842
13	I cannot do without my mobile phone because I always need it in my agricultural work.	4.15	0.90	0.830
14	The programs I use to make production calculations save me from relying on other people.	4.11	0.98	0.822
15	Most of the calculations related to agriculture I tabulate using the computer.	4.07	0.82	0.814
16	I compare what I encounter on the farm with the pictures on the Internet.	4.06	0.90	0.812
17	Most of the problems I face in my agricultural work I find a solution for using search engines.	4.05	1.10	0.810
18	I cannot do without the Internet on my mobile phone while I work as a farmer.	4.02	1.10	0.804
19	I always search for the type of diseases that affect my crops in search engines.	4.01	0.84	0.802
20	I rely on social media to obtain agricultural information.	4.00	1.10	0.800

The low-ranked statements were associated with specialised applications of digital technology. Using computers for performing agricultural calculations, comparing farm issues with images on the Internet and searching for plant diseases using search engines were ranked lower on the list. “I depend on social media for getting agricultural information” was the last statement in the list with a mean rating of 4.00 and a relative weight of 0.800. Even the least favoured statement had a higher mean value, suggesting that social media was used, though less than other activities such as searching the Internet, using mobile phones and having up-to-date information.

Random forest regression model for digital technology use

The Random Forest regression model was estimated using age, education, origin, agricultural information sources and digital technology training as independent variables, with digital technology use score as the dependent variable. The dataset was split into training and test sets at 80:20 and out-of-bag validation was used as an additional internal validation procedure. The model achieved a training R^2 of 0.6879, with MAE and RMSE values of 0.0402 and 0.0552, respectively, indicating a good in-sample fit. However, the testing R^2 was lower at 0.3920, with MAE and RMSE values of 0.0898 and 0.1146, respectively. Out-of-bag (OOB) validation yielded an R^2 of 0.2830, with MAE and RMSE values of 0.0901 and 0.1125, respectively. These results indicate that the model explained 39.20% of the variation in unseen observations and 28.30% under OOB validation, suggesting moderate predictive performance. The disparity between the training and validation results suggests some degree of overfitting. Therefore, the testing and OOB results are considered more reliable indicators of model generalisation than the training R^2 alone.

Figure 1 presents the random forest feature importance scores, which show the relative contribution of each predictor to improving model prediction. Age was the most important predictor, with an importance score of 0.5428, indicating its strongest contribution to differences in digital technology use among rural leaders. Education ranked second with a score of 0.1906, followed by information sources with 0.1692. Training on digital technology had a comparatively lower importance score of 0.0688, while origin was the least important predictor with a score of 0.0287. This suggests that personal characteristics and exposure to information sources were more influential than origin in predicting digital technology use.

Figure 2 presents the SHAP summary plot, which offers a respondent-level interpretation of the same random forest model. While Figure 1 ranks predictors by overall importance, Figure 2 illustrates how each predictor contributed to the predicted digital technology use score for individual respondents. In the SHAP plot, each point represents the predictor contribution of one respondent. Positive SHAP values indicate that a predictor increased the predicted digital technology use score, whereas negative SHAP values indicate a reduction. The wider spread of points for age demonstrates that age had the strongest and most variable influence on model output. Education and information sources also showed visible contributions, confirming their importance in shaping digital technology use. Training and origin had narrower SHAP distributions, indicating comparatively weaker effects.

Reasons for not using digital technology

The results in Table 2 showed that the high prices of modern, high-quality mobile phones were the most frequently reported reason for not using digital technology to obtain agricultural information. This constraint was reported by 65 respondents, accounting for 64.4 per cent. The financial cost of Internet use ranked second, with 56 respondents (55.4 per cent). These findings indicated that economic barriers were the major constraints limiting the effective use of digital technology among rural leaders.

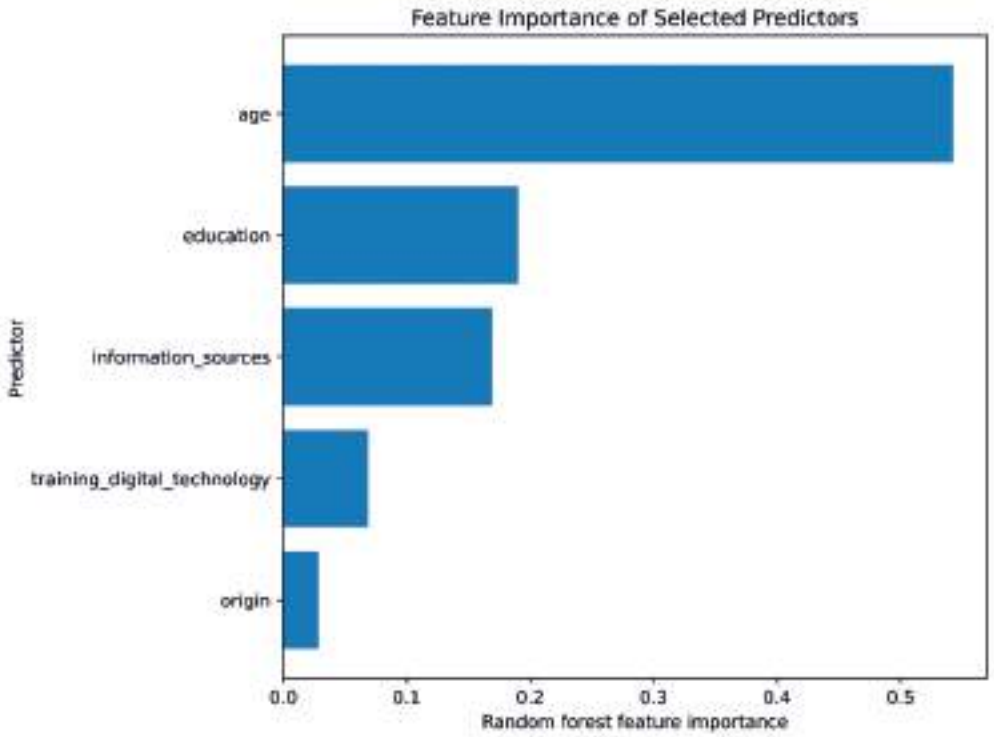


Figure 1. Random forest feature importance of predictors of digital technology use

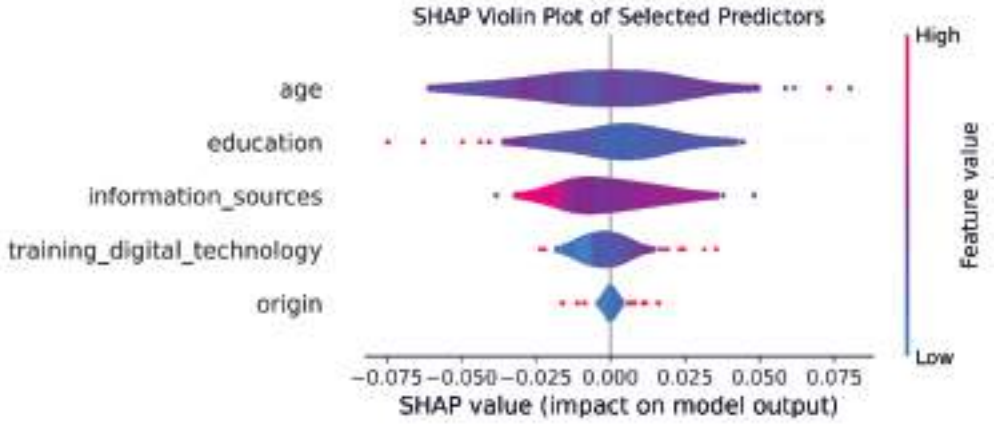


Figure 2. SHAP summary violin plot showing predictor contribution to digital technology use

Table 2. Reasons for not using digital technology to obtain agricultural information

Reason	Percentage
High prices of modern quality mobile phones	64.4
The financial cost of using the Internet	55.4
Lack of sufficient time to use digital technology	39.6
Lack of computer availability in the field	30.7
Lack of consistency in the effectiveness of digital technology in obtaining agricultural information	41.6
I do not know how to use the Internet to obtain agricultural information	34.7
I do not have enough experience to use a computer	30.7
I prefer to use the phone for communication only	22.8

The lack of consistency in the effectiveness of digital technology for obtaining agricultural information was reported by 42 respondents (41.6 per cent), while the lack of sufficient time to use digital technology was reported by 40 respondents (39.6 per cent). 35 respondents (34.7 per cent) reported a lack of knowledge about using the Internet for agricultural information. Lack of computer availability in the field and insufficient computer-use experience were each reported by 31 respondents, accounting for 30.7 per cent. The least reported reason was a preference for using the phone only for communication, reported by 23 respondents (22.8 per cent).

DISCUSSION

Rural leaders in Nineveh effectively used digital technology to acquire agricultural information, as evidenced by very high mean scores across all twenty statements. Digital technology has become a crucial component of their agricultural information-seeking behaviour, particularly for obtaining timely, up-to-date information. This suggests leaders value its speed, accessibility and ability to provide timely information at the farm level, aligning with Mukherjee and Jha (2024) observed that farmers use ICTs for information gathering. Digital technology was also considered useful

for practical agricultural work. The moderate ranking of computerised calculations, image analysis and disease search indicates that more complex applications were less utilised. This supports Panda et al., (2019) and Chaturvedi & Vatta (2025) findings that farmers prefer digital technology for simple farm processes over technical purposes.

The random forest regression model accounted for a considerable amount of variance in digital technology usage. Age was the top predictor, followed by education and sources of information. The significance of age implies that rural leaders' digital behaviour is influenced by personal experience, decision-making roles and familiarity with farming environments. Education is also crucial, as educated individuals are expected to analyse digital agricultural information efficiently (Chandra et al., 2024). Information sources strongly influenced digital technology use, with leaders connecting to diverse agricultural information sources more likely to use digital tools effectively. This suggests digital media complements existing extension, interpersonal and institutional information systems, rather than operating in isolation (Pradhan et al., 2025). Training on digital technology had a meaningful but comparatively lower contribution. Internet access and digital training significantly improve farmers' adoption of sustainable agricultural practices, productivity and welfare (Sher et al., 2025). Sahoo et al. (2025) reported that ICT-oriented training improved the capacity of extension personnel and farmers to use digital tools for information dissemination and advisory support.

Constraints further explained the limits of digital technology use. High prices of modern mobile phones and the cost of Internet use were the leading barriers. Satapathy et al. (2024) also identified cost, access and skill-related barriers as major constraints in ICT adoption in agriculture. Lack of time, limited computer availability, inadequate Internet knowledge and limited computer experience indicated a financial, infrastructural and skill-based digital divide (Sondara et al., 2023). Sen et al. (2024) similarly observed that digital extension adoption depended on device access, digital skills and confidence in using services.

Digital technology created opportunities for rural leaders to access agricultural information, but its effective use depended on education, exposure to information, training and affordability. Digital extension programmes in Nineveh should therefore focus on practical digital literacy, low-cost access, local-language content and field-level support. Inclusive extension strategies are required to ensure that digitally less-prepared farmers are not excluded from emerging agricultural information systems (Saha et al., 2024). The wider adoption of smart agricultural technologies also requires user readiness, institutional support and locally suitable implementation pathways (Prusty et al., 2025).

The study has certain limitations. Although predictor selection was guided by diffusion and digital-divide perspectives, the study did not directly measure all constructs commonly used in formal technology-adoption models. Therefore, the findings should be interpreted as explaining selected socio-demographic, informational, and capacity-related correlates of digital technology. Future studies may include these constructs to develop a more comprehensive model of digital technology adoption among rural agricultural leaders, potentially applying technology-acceptance frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine how performance expectancy, effort expectancy, facilitating conditions, price value and behavioural intention shape adoption (Zhang et al., 2024).

CONCLUSION

The findings indicate that the use of digital technology by rural leaders to obtain agricultural information is favourable. Digital technology is used to acquire the latest, up-to-date agricultural information, to make farm work easier and to support agricultural decision-making. Age is a significant predictor of digital technology use, followed by educational qualification and sources of information. The major barriers encountered are the high cost of modern mobile phones, high Internet rates, limited time, insufficient computers and limited digital technology experience. The study contributes to digital agricultural extension by showing that rural leaders can serve as strategic entry points for strengthening digital information flow in farming communities. Improving their digital capacity may improve the reach, credibility and local relevance of agricultural advisory services. Therefore, extension organisations should develop village-level digital leadership models that combine affordable internet access, practical digital literacy training, locally relevant agricultural content and regular institutional support.

DECLARATIONS

Ethics approval and informed consent: Throughout the study, the respondents were asked for their informed consent.

Conflict of interest: The research was carried out without any financial or commercial ties that might be seen as a potential conflict of interest, according to the authors. The authors affirm that they carefully examined, amended and edited the content as necessary when preparing this work. The final content of this publication is entirely the authors' responsibility.

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Research Article

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Visitor Behaviour and Economic Valuation of Spiritual Tourism in Rameshwaram Island, India

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HIGHLIGHTS

- Travel expenditure negatively influenced visitation frequency among spiritual tourists.
- Visitor satisfaction positively affected revisit behaviour and tourism participation.
- Spiritual tourism generated substantial consumer surplus and regional economic benefits.
- Improved tourism infrastructure and awareness programmes supported sustainable pilgrimage tourism.

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ABSTRACT

The study evaluated visitor behaviour and the economic importance of spiritual tourism in Rameshwaram Island during 2025 using the Individual Travel Cost Method (ITCM). Primary information was obtained from 400 spiritual tourists through a field survey conducted at important pilgrimage centres in the study area. Tourism demand and visitation patterns were estimated using Poisson and Negative Binomial regression approaches. The Negative Binomial specification was found to be more suitable for explaining tourist visitation behaviour. Travel expenditure showed an inverse relationship with visitation frequency, indicating that higher travel costs reduced repeat visits. In contrast, visitor satisfaction positively influenced tourism participation and revisit intention, while income showed a favourable association with tourism demand. The estimated consumer surplus was Rs. 20,833 per trip, reflecting substantial welfare gains derived from spiritual tourism. The findings also indicated that spiritual tourism contributed notably to the regional economy through tourism expenditure and service-related activities. The study emphasised the need for effective tourism planning, visitor awareness programmes, infrastructure improvement and extension support for promoting sustainable spiritual tourism development in Rameshwaram Island.

INTRODUCTION

Spiritual tourism contributes substantially to local economic development through employment generation, livelihood support and preservation of cultural heritage resources (UNWTO, 2024). It has also emerged as an important component of sustainable rural and regional development in several pilgrimage destinations across India (Patial et al., 2025). Pilgrimage centres support economic activities related to hospitality, transport and local commerce. In India, pilgrimage tourism has expanded because of historically important religious destinations (Ministry of Tourism, 2024). Spiritual tourism encompasses travel motivated by religious beliefs, spiritual interests and faith-oriented experiences, where visitors seek personal meaning, spiritual enrichment and participation in sacred

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practices associated with religious destinations. In the context of the present investigation, spiritual tourists referred to pilgrims visiting the Ramanathaswamy Temple and other religious sites in Rameshwaram primarily for worship, pilgrimage and related spiritual activities. Among these destinations, Rameshwaram Island in Tamil Nadu occupies a prominent position because of the religious significance of the Ramanathaswamy Temple and its association with Hindu spiritual traditions. Spiritual tourism generates cultural and social benefits for pilgrims and communities. These activities strengthen cultural identity and enhance visitor experiences (Romanazzi et al., 2023). Since many of these benefits are not directly traded in conventional markets, economic valuation approaches are useful for estimating their contribution to tourism development and policy planning (Yao & Wallace, 2024). Tourism participation is shaped by various socio-economic and behavioural attributes, making their assessment important for destination planning, management and tourism extension initiatives. Similar extension interventions were reported in Indian Agri-tourism and rural tourism studies (Krishna et al., 2019). Multi-stakeholder participation in tourism-linked livelihood promotion was emphasised (Krishna et al., 2021).

Empirical evidence indicates that tourism experience, destination image and visitor satisfaction positively influence revisit intention and tourist participation (Acharya et al., 2023; Sugiama et al., 2024). Tourism expenditure contributes to regional economic growth and sustainability (Cárdenas-García et al., 2024). Increasing tourist arrivals at religious destinations have intensified the need for improved infrastructure and visitor management systems. Despite its growing importance, empirical evidence on visitor behaviour, tourism demand and welfare benefits remains limited in many pilgrimage destinations. Previous studies have mainly focused on destination development, pilgrimage management, visitor satisfaction and revisit intention (Acharya et al., 2023; Sugiama et al., 2024). However, limited attention has been given to the combined assessment of visitor behaviour and the economic value of spiritual tourism through economic valuation approaches. In the context of Rameshwaram Island, information on tourism demand, visitation behaviour and visitor welfare benefits remains scarce, restricting evidence-based planning, infrastructure development and policy formulation. The Travel Cost Method (TCM) is widely used for estimating recreational demand and consumer surplus associated with tourism destinations (Adu et al., 2024; Wubalem et al., 2023). Earlier valuation studies further reported that increasing travel expenditure reduces visitation frequency, whereas improved visitor satisfaction encourages repeat visits (Hashim, 2023; Ramadan & Rantini, 2024). Therefore, the present study investigates visitor behaviour and estimates the economic value of spiritual tourism in Rameshwaram Island using the Individual Travel Cost Method.

METHODOLOGY

The study was purposively undertaken in Rameshwaram Island, Tamil Nadu, owing to its prominence as one of the major pilgrimage destinations attracting visitors throughout the year. Primary data were collected during 2025 from tourists visiting major pilgrimage locations in the study area. A total of 400 spiritual tourists were selected using a convenience sampling method. Data on visitation frequency, travel expenditure, visitor satisfaction, income, education and duration of stay were obtained through a pre-tested interview schedule.

Visitor behaviour was operationalised using visitation frequency, travel expenditure, visitor satisfaction and duration of stay. Visitor satisfaction was measured using a five-point Likert scale ranging from 1 (very dissatisfied) to 5 (very satisfied), covering transportation facilities, accommodation, cleanliness, temple facilities, safety and overall pilgrimage experience. Before conducting the statistical analysis, the reliability of the visitor satisfaction scale was evaluated using Cronbach's alpha. The obtained alpha value of 0.78 demonstrated an acceptable degree of internal consistency among the satisfaction-related items, indicating that the scale was sufficiently reliable for further analysis. The interview schedule was pre-tested before the final survey. Respondents aged 18 years and above who visited the destination for pilgrimage purposes and were willing to participate in the survey were included in the sample. Convenience sampling was employed as pilgrims were highly mobile across survey locations, and a comprehensive sampling frame was unavailable. The study was conceptually structured to examine the influence of socio-economic characteristics, travel-related factors and visitor satisfaction on pilgrimage participation behaviour. Tourism demand was represented by visitation frequency and used to derive consumer surplus and economic value.

Tourism demand and welfare benefits were assessed using the Individual Travel Cost Method (ITCM), a commonly used approach for valuing recreational and tourism resources (Mayer & Woltering, 2018; Cetin et al., 2021). The Individual Travel Cost Method is founded on the principles of welfare economics and consumer behaviour theory. The expenditure incurred by visitors to reach and experience a destination is treated as an indirect measure of the value they place on that visit. By examining the relationship between travel expenditure and visitation frequency, a tourism demand function can be estimated, which subsequently enables the calculation of consumer surplus as an indicator of the net welfare benefits derived from the tourism experience.

The tourism demand function was specified as:

$$Trips_i = f(TC_i, Age_i, Income_i, Edu_i, Sat_i, Stay_i)$$

Where, $Trips_i$ denotes the number of visits made by individual i; TC_i represents travel cost; Age_i denotes age; $Income_i$ represents annual income; Edu_i denotes education level; Sat_i represents visitor satisfaction; $Stay_i$ denotes length of stay.

The empirical tourism demand model was expressed as:

$$Trips_i = \beta_0 + \beta_1 TC_i + \beta_2 Age_i + \beta_3 Income_i + \beta_4 Edu_i + \beta_5 Sat_i + \beta_6 Stay_i + \varepsilon_i$$

Where, β_0 is the intercept; β_1, β_2,..., β_6 are parameters to be estimated; ε_i is the random error term.

Since visitation frequency represented count data, Poisson and Negative Binomial regression models were estimated for tourism demand analysis (Hashim, 2023). The Poisson regression model was initially estimated as:

$$E(Trips_i \mid X_i) = \lambda_i$$

However, as the visitation data exhibited over-dispersion, the Negative Binomial regression model was considered more

appropriate. The variance specification was expressed as:

$$Var(Trips_i \mid X_i) = \lambda_i + \alpha\lambda_i^2$$

Where, α represents the over-dispersion parameter. Model selection was based on log-likelihood and Akaike Information Criterion (AIC) values.

Consumer surplus was estimated using the inverse of the travel cost coefficient:

$$CS = -\frac{1}{\alpha_{TC}}$$

where, *CS* denotes consumer surplus per trip and α_{TC} represents the travel cost coefficient.

The recreation value per visitor was estimated as:

$$RV_{visitor} = CS \times \overline{V}$$

Where, $RV_{visitor}$ denotes recreation value per visitor; CS represents consumer surplus per trip; $\overline{V}$ denotes the average number of visits.

The total recreation value generated through spiritual tourism was estimated as:

$$TRV = CS \times N$$

Where, *TRV* represents total recreation value and *N* denotes annual visitor arrivals. Descriptive statistics were used to examine visitor and travel characteristics, whereas Poisson and Negative Binomial regression models were applied to estimate tourism demand. Consumer surplus and recreation value were subsequently derived using the Individual Travel Cost Method. The data were analysed using IBM SPSS Statistics Version 29.0.0.0.

RESULTS

Visitor behaviour and tourism demand

Table 1 summarised the descriptive statistics relating to spiritual tourism variables collected from pilgrims visiting Rameshwaram Island. The average visitation frequency was estimated at 2.35 trips annually, whereas the mean travel expenditure per trip amounted to Rs. 4520.40. Pilgrims reported a satisfaction score of 4.70 and the average duration of stay was estimated at 1.80 days. The findings showed repeated pilgrimage participation because of the religious importance and cultural relevance of the destination. Pilgrims reported a comparatively higher level of satisfaction with their overall pilgrimage experience.

The comparative performance of the Poisson and Negative Binomial specifications was presented in Table 2. The Negative Binomial model recorded a comparatively higher log-likelihood value (-206.92) and lower Akaike Information Criterion (AIC) value (427.84), indicating improved explanatory performance for tourism visitation behaviour. The estimated over-dispersion parameter (Alpha = 0.41) suggested that the variance exceeded the corresponding mean value of visitation frequency, thereby supporting the suitability of the Negative Binomial specification for tourism demand estimation. The findings indicated that visitation data associated with spiritual tourism exhibited over-dispersion, making the Poisson specification comparatively less suitable for analysing tourism participation behaviour. The Negative Binomial model, therefore, provided a more reliable explanation of pilgrimage tourism demand in the study area. The results confirmed the suitability of the Negative Binomial model for analysing tourism participation behaviour.

The estimated coefficients of the Negative Binomial tourism demand model were presented in Table 3. Travel expenditure showed a negative and significant relationship with visitation frequency. The estimated travel cost coefficient (-0.000048) indicated that increasing travel expenditure reduced pilgrim visits to Rameshwaram

Table 2. Model Selection for Tourism Demand

Indicator	Poisson	Negative Binomial	Preferred Model
Log Likelihood	-212.47	-206.92	Negative Binomial
AIC	438.94	427.84	Negative Binomial

Source: Author's computation (2025)

Table 3. Negative Binomial Estimates of Spiritual Tourism Demand

Variables	Coefficient	Std. Error	z-value	p-value
Travel Cost	-0.000048***	0.000013	-3.69	0.000
Age	0.019***	0.007	2.71	0.007
Income	0.000003	0.000004	0.75	0.454
Education Level	0.041	0.044	0.93	0.352
Satisfaction	0.296***	0.068	4.35	0.000
Length of Stay	0.107***	0.040	2.68	0.007
Constant	0.871***	0.269	3.24	0.001
Log Likelihood	-206.92	-	-	-
LR Chi-square	63.14	-	-	-
Prob > Chi²	0.000	-	-	-
Pseudo R²	0.132	-	-	-
Alpha (Overdispersion)	0.41	-	-	-

Note: *** Significant at p < 0.01
Source: Author's computation (2025)

Table 1. Descriptive Statistics of Spiritual Tourism Variables (n=400)

Variable	Description	Mean	Std. Dev.	Min	Max
Trips per Year	Number of annual visits	2.35	1.32	1	6
Travel Cost (Rs.)	Total expenditure per trip	4520.40	1758.60	1200	7800
Age (Years)	Age of respondents	38.90	10.15	22	58
Income (Rs. lakh/year)	Annual household income	3.07	1.01	1.04	5.40
Education Level	Educational attainment	3.20	1.02	1	4
Satisfaction	Visitor satisfaction score	4.70	0.64	3	5
Length of Stay (Days)	Duration of stay	1.80	0.73	1	3

Source: Primary survey data (2025)

Island. The lower coefficient magnitude suggested comparatively less sensitivity of spiritual tourism demand to moderate travel cost variations. Age recorded a positive and significant relationship with tourism participation, indicating comparatively higher visitation among older pilgrims. Income and education level showed positive but statistically non-significant relationships with visitation behaviour. Tourist satisfaction emerged as an important factor influencing visitation behaviour. The positive and significant coefficient (0.296) suggested that satisfactory tourism experiences and improved visitor facilities encouraged repeat visitation. Length of stay also showed a positive association with tourism participation. Overall, the regression estimates indicated that spiritual tourism demand was influenced by economic, demographic and experiential factors, with tourist satisfaction exerting a comparatively stronger effect on visitation behaviour.

The marginal effects estimated from the Negative Binomial model were presented in Table 4. Tourist satisfaction produced the highest positive marginal effect (0.584), indicating that improved visitor experience considerably increased expected visitation frequency. Travel expenditure generated a negative marginal effect (-0.000096), confirming the inverse association between travel expenditure and tourism participation. Age and duration of stay positively influenced visitation behaviour, whereas income and education level were not statistically significant. The findings showed that experiential and behavioural factors played an important role in shaping tourism participation in pilgrimage destinations.

Table 4. Marginal Effects of Tourism Demand Variables

Variables	Marginal Effect	Std. Error	z-value	p-value
Travel Cost	-0.000096***	0.000025	-3.84	0.000
Age	0.038***	0.014	2.71	0.007
Income	0.000006	0.000007	0.86	0.389
Education Level	0.082	0.088	0.93	0.352
Satisfaction	0.584***	0.136	4.29	0.000
Length of Stay	0.211***	0.078	2.70	0.007

Note: *** Significant at p < 0.01; *Source:* Author's computation (2025)

Welfare estimates and economic value of spiritual tourism

The elasticity estimates were presented in Table 5. The estimated travel cost elasticity value (-0.217) indicated relatively inelastic tourism demand, suggesting that pilgrimage tourism participation remained less responsive to moderate variations in travel expenditure. The lower responsiveness to travel cost reflected the influence of spiritual motivation and religious attachment on visitation decisions. These results further showed that pilgrimage tourism participation in Rameshwaram Island was influenced more strongly by religious and cultural motivations than by economic considerations.

Table 5. Travel Cost Demand Elasticity

Tourism Type	Travel Cost Coefficient	Mean Travel Cost (Rs.)	Elasticity
Spiritual Tourism	-0.000048	4520.40	-0.217

Source: Author's computation (2025)

The semi-elasticity estimates shown in Table 6 indicated that a Rs. 1000 increase in travel expenditure reduced visitation frequency by nearly 4.8 per cent. The estimates demonstrated comparatively stable pilgrimage participation despite moderate increases in travel-related expenditure. The findings indicated that pilgrimage tourism participation remained comparatively less sensitive to moderate changes in travel expenditure because of spiritual motivation and religious commitment among visitors.

Table 6. Tourism Demand Semi-Elasticity

Tourism Type	Travel Cost Coefficient	Change in Trips for Rs. 1000 Increase
Spiritual Tourism	-0.000048	-4.8%

Source: Author's computation (2025)

The welfare estimates associated with spiritual tourism were presented in Table 7. The estimated consumer surplus per trip amounted to Rs. 20,833, reflecting welfare benefits obtained by pilgrims beyond actual travel expenditure. The annual consumer surplus per visitor was estimated at Rs. 48,958, while the aggregate consumer surplus generated through spiritual tourism was estimated at Rs. 17,708 crores. These estimates highlighted the economic significance of pilgrimage tourism through tourism-related expenditure and associated service-sector activities in the study area.

Figure 1 illustrates the recreation demand curve for spiritual tourism in Rameshwaram Island. The downward-sloping curve indicates that visitation frequency declines as travel expenditure increases, confirming the inverse relationship between travel cost and tourism demand. The shaded area beneath the curve represents consumer surplus, reflecting the welfare benefits obtained by pilgrims beyond their actual travel expenditure. The relatively gentle slope further suggests that spiritual tourism demand is less responsive to moderate changes in travel expenditure.

The summary welfare indicators relating to spiritual tourism were provided in Table 8. The estimates indicated comparatively higher visitation frequency, lower price sensitivity and substantial welfare gains associated with pilgrimage tourism activities. The estimated total consumer surplus further demonstrated the economic importance of spiritual tourism in supporting tourism-linked services and regional economic activities. The findings collectively indicated that spiritual tourism in Rameshwaram Island generated notable welfare and economic benefits through tourism expenditure, tourism participation and pilgrimage-related activities.

Table 7. Consumer Surplus and Economic Value of Spiritual Tourism

Tourism Site	Travel Cost Coefficient	Consumer Surplus per Trip (Rs.)	Annual Visitors	Total Consumer Surplus (Rs. crore)
Spiritual Tourism	-0.000048	20,833	8,500,000	17,708.00

Source: Author's computation (2025)

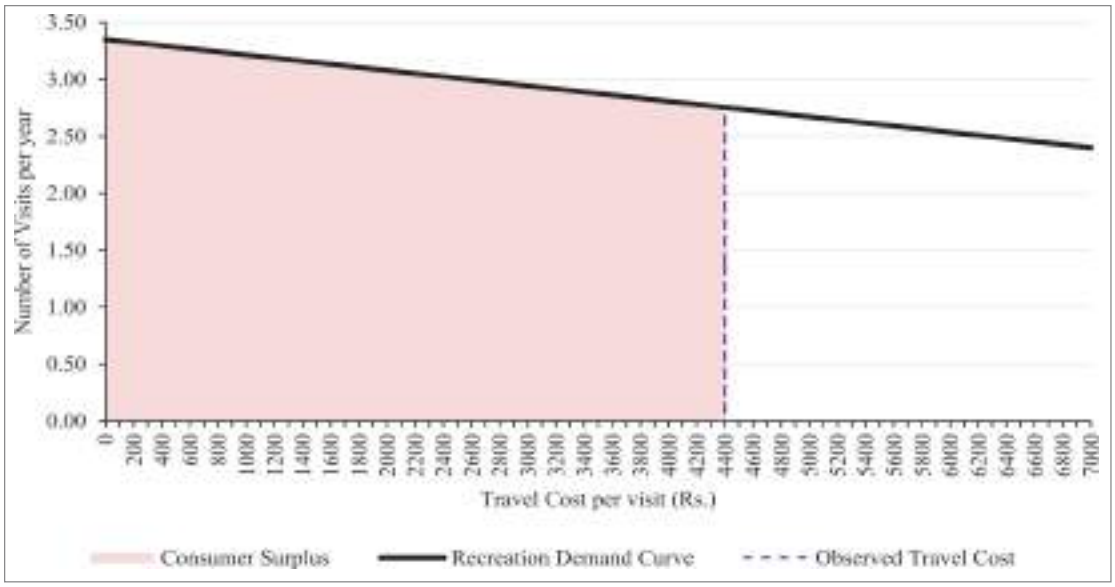


Figure 1. Recreation demand curve with consumer surplus for spiritual tourism

Table 8. Summary of Welfare and Demand Indicators

Indicator	Spiritual Tourism
Mean Trips per Year	2.35
Mean Travel Cost (Rs.)	4520.40
Travel Cost Coefficient	-0.000048
Travel Cost Elasticity	-0.217
Semi-Elasticity (Trips change for Rs. 1000 increase)	-4.8%
Consumer Surplus per Trip (Rs.)	20,833
Average Annual Trips	2.35
Annual Consumer Surplus per Visitor (Rs.)	48,958
Annual Visitors	8,500,000
Total Consumer Surplus (Rs. crore)	17,708

DISCUSSION

Pilgrimage travel is often driven by faith-based motivations that extend beyond conventional recreational considerations, encouraging visitors to maintain a continued connection with spiritually significant destinations. The model selection results indicated that the Negative Binomial model provided a comparatively better explanation of tourism visitation behaviour than the Poisson specification because of over-dispersion in visitation data, thereby supporting the suitability of count-data regression approaches for tourism demand estimation (Hashim, 2023; Ramadan & Rantini, 2024). The negative association observed between travel expenditure and visitation frequency indicated that increasing travel costs reduced tourism participation. This relationship is consistent with economic demand theory, which suggests that participation tends to decline as the cost of accessing a service or destination increases. However, the comparatively lower elasticity value suggested that spiritual tourism demand remained relatively stable despite moderate increases in travel expenditure. This indicates that pilgrimage decisions were influenced not only by monetary considerations but also by faith, religious commitment and spiritual fulfilment. Such non-economic motivations may reduce visitor sensitivity to travel expenditure and contribute to relatively stable visitation behaviour, which is consistent with the observations of Yao and Wallace (2024). Tourist satisfaction showed a positive influence on revisit behaviour, indicating that satisfactory tourism experiences encouraged repeated visitation among pilgrims. A favourable pilgrimage experience can enhance perceived benefits, strengthen emotional attachment to the destination and increase the likelihood of future visits. Visitor satisfaction therefore acts as an important behavioural factor that reinforces destination loyalty and continued tourism participation. The positive role of visitor satisfaction in encouraging destination loyalty and repeat visitation has also been documented by Kim (2018) and Sugiama et al. (2024). The positive relationship observed between duration of stay and tourism participation suggested that pilgrims spending comparatively longer periods at the destination were more likely to revisit spiritual tourism sites. Longer stays may provide greater opportunities for spiritual engagement, participation in religious activities and interaction with the cultural environment. These experiences can strengthen destination attachment and encourage future pilgrimage participation (Romanazzi et al., 2023; Santos et al., 2021). The marginal effects further confirmed the dominant influence of visitor satisfaction on pilgrimage tourism participation. These findings emphasised the importance of improving visitor experience, tourism facilities and support services for sustaining pilgrimage tourism participation.

The welfare estimates highlighted the substantial benefits generated through spiritual tourism activities in Rameshwaram Island. The recreation demand curve illustrated the inverse relationship between travel expenditure and visitation frequency, while the comparatively flatter demand curve indicated lower sensitivity of spiritual tourism demand to moderate increases in travel expenditure. The shaded consumer surplus area represented substantial welfare benefits obtained by pilgrims beyond actual travel expenditure. From a welfare economics perspective, consumer surplus represents the difference between the value perceived by visitors and the actual expenditure incurred to access a destination. The comparatively high consumer surplus estimated in the present study suggests that pilgrims derived substantial benefits from the pilgrimage experience that extended beyond the direct costs incurred

during travel. These benefits included spiritual fulfilment, cultural enrichment, emotional attachment and personal satisfaction associated with visiting sacred destinations. The distinctive nature of pilgrimage tourism implies that travel decisions are influenced not only by economic considerations but also by faith, devotion and religious commitment. Consequently, the overall value perceived by pilgrims may exceed actual travel expenditure, resulting in higher welfare gains and consumer surplus estimates. These findings highlight the broader social, cultural and spiritual value generated through participation in spiritual tourism activities. Comparable evidence relating to recreation demand and welfare benefits was reported by Adu et al. (2024). The aggregate consumer surplus highlighted the contribution of spiritual tourism towards tourism-linked enterprises, local livelihood opportunities and regional service-sector activities. Higher consumer surplus values indicate that visitors attach considerable value to their participation in spiritual tourism activities, thereby reflecting the broader economic and social significance of pilgrimage destinations (Parsons, 2017). Comparable welfare benefits associated with tourism valuation were reported by Wubalem et al. (2023), while Cárdenas-García et al. (2024) documented the contribution of tourism activities towards regional economic development and livelihood support. From an extension education perspective, the findings offer valuable insights for developing awareness initiatives, visitor information support and community-oriented tourism programmes. The evidence generated through the assessment of visitor behaviour and economic value can assist extension personnel, local institutions and tourism stakeholders in designing educational activities, encouraging community involvement and promoting sustainable tourism practices in pilgrimage destinations. Strengthening tourism information dissemination systems, sanitation awareness campaigns and tourism-related support services could improve visitor satisfaction and promote sustainable tourism development. Community participation and stakeholder engagement can further support effective destination management and enhance the long-term sustainability of pilgrimage tourism. Capacity-building initiatives for local stakeholders and tourism service providers may further strengthen destination management and improve the quality of services offered to visitors. Similar stakeholder-oriented and participatory tourism approaches were emphasised by Slathia et al. (2015) and Krishna et al. (2021). The findings therefore suggested that strengthening tourism infrastructure, sanitation management systems, visitor guidance services and extension-based awareness programmes could contribute towards sustainable spiritual tourism development and effective management of pilgrimage destinations in the study area.

CONCLUSION

The study analysed the economic contribution and visitation behaviour related to spiritual tourism in Rameshwaram Island by applying the Individual Travel Cost Method. The results indicated that increasing travel expenses reduced the frequency of tourist visits, while positive visitor experience and satisfaction encouraged revisits and greater tourism involvement. The Negative Binomial regression model was found appropriate for interpreting tourism demand because the visitation pattern varied considerably among respondents. The estimated consumer surplus of Rs. 20,833 per visit reflected the welfare benefits obtained by pilgrims through spiritual tourism activities. The findings also showed that pilgrimage tourism supported regional economic growth through transportation services, accommodation facilities, local business activities and tourism-related employment opportunities. Strengthening tourism infrastructure, sanitation practices, visitor guidance services, awareness activities, stakeholder coordination and community participation would therefore help improve pilgrimage management, enhance visitor satisfaction and support sustainable spiritual tourism development in the study area over the long term.

DECLARATIONS

Ethics approval and informed consent: Throughout the study, the respondents were asked for their informed consent.

Conflict of interest: The research was carried out without any financial or commercial ties that might be seen as a potential conflict of interest, according to the authors. The authors affirm that they carefully examined, amended and edited the content as necessary when preparing this work. The final content of this publication is entirely the authors' responsibility.

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Research Article

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Agricultural Mechanization and its Problems in Gauradaha Municipality of Jhapa District, Nepal

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HIGHLIGHTS

- Agriculture mechanization can lower costs, workloads and operating times
- Cultivars and Threshers were the most popular and widely used farm machines
- Large-sized farm holders and commercial farmers adopt farm mechanisation

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ABSTRACT

Mechanisation can lower labour costs, workloads, and operating times, which eventually boosts agricultural productivity and output. The study aimed to assess the status of mechanisation, problems of adoption of mechanisation, and its impact was conducted during 2024-25. Purposive random sampling of 120 farmers from four wards of the Gauradaha municipality of Jhapa was used and collected data on socio-economic status, problems, and the impact of farm mechanisation. Chi-square test was used to determine the relationship between selected variables. This study suggested that 100% farmers used cultivators and threshers, followed by 79.17% pump sets/motor, 55% combine harvester, 42.5% Reaper and 11.7% others (Power tiller, Corn sheller, Corn harvester, Driller, Paddy straw cutter). Subsidy to buy farm machinery was obtained by 10% of farmers only. Larger holdings of farmers' land had a positive significance in the use and adoption of farm mechanisation.

INTRODUCTION

Agricultural mechanisation (AM) involves using tools and machinery to optimize production at any stage. Its primary goal is resource efficiency, which generates significant socio-economic benefits for farmers (Emani et al., 2008; GC et al., 2009). Mechanization can lower labour costs, workloads, and operating time, which eventually boosts agricultural productivity and output (Paudel et al., 2019; Daum & Birner, 2020). For every 1% increase in the levels of mechanization, the yields of all crops, grain crops, and cash crops increase by 1.215, 1.594, and 0.435%, respectively (Peng et al., 2022). Effective mechanization offers significant resource efficiency, potentially reducing seed use by 15–20%, fertiliser by 20–30%, and labour by 5–20%, while boosting productivity by up to 20% (Singh, 2008; Tiwari et al., 2019; Mehta et al., 2023). However, Nepal's mechanization rate remains low at 20-25 %, trailing significantly behind global leaders like the US (95%), Russia (80%), and China (48%) (Mehta et al., 2023; Baruah et al., 2025).

Most of farmers in Nepal are small-sized farm holders with an average of 0.8 hectares (Gauchan & Shrestha, 2017) that forces them to practice subsistence farming and lesser adoption of farm mechanisms. Adopting farm machinery is also hampered by farmers' poor financial circumstances (Uchelegit et al., 2020). Most of Nepal's farm power requirements are met by human (40.5%) and animal (36.3%) power, with mechanical power making up a meager 23.2% of the total (Ranabhat et al., 2025). This indicates that mechanization in the country is still in its infancy (Shrestha, 2012).

Agricultural mechanization should contribute to a sustainable increase in productivity and cropping intensity so that the planned

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growth rates in agricultural production are achieved (Mehta et al., 2014). The lack of agricultural labour and their increased daily wage have resulted in the demand for agricultural mechanization in Nepal. Hence, the migration of youth can be regarded as a major driver for the increasing demand for agricultural mechanization (Shrestha, 2022). Only over one-fifth of the power utilized in Nepal is thought to be used by machines (Shrestha, 2012). Approximately 90% of the mechanical power in use today is concentrated in Terai that is accessible to the market. Due to the challenges of moving large machinery and utilizing it on narrow terraces, mechanization is minimal in the hilly and mountainous regions. However, the employment of tractors, power tillers, pump sets, and threshers has increased recently due to increased road connectivity in rural hills and mountains. Shrestha (2012) also reported lack of well-defined policy regarding agricultural mechanization has resulted in a lack of efficiency in meeting the needs of farming communities and national development objectives related to the commercialization of agriculture in Nepal. Previous researcher Shrestha (2022); Ranabhat et al. (2025) etc have emphasized policy over the first-hand perspectives and perceptions of farmers regarding mechanization. So, objectives of this research were to explore status of farm mechanism, impact and problems associated with adoption of farm mechanism.

METHODOLOGY

Gauradaha Municipality of Jhapa was selected for this study as represented in Figure 1. Four wards were selected purposely for survey purposes. These wards were selected due to the availability of roads and accessibility of the agriculture service centre. Besides, farmers cultivate a diverse range of crops such as rice, wheat, maize, and cash crops like tea, and jute. This variety offers a broad perspective on the implementation of agricultural mechanization.

Purposive random sampling was used for data collection. Inclusion criteria of farmers in this study that farmers have at least 0.8 hectare of land for agricultural purposes. Ward number 1,2,3, and 4 were selected and equal number of samples were collected. Altogether 120 samples were taken by using Slovin's Formula ($n=N/1+Ne^2$, where N is population size) was used for sample size estimation. This study used a descriptive sample survey research approach to learn about how farmers use different farm machinery. Quantitative data were used to assess the status of farm mechanization. Information on mechanization was collected through a structured survey questionnaire. Before performing the survey, the interview schedule was checked to ensure its clarity, reliability and validity. 5% of the total respondents were interviewed for pre-testing, just to reduce the chances of mistakes. After the pretesting, some adjustment was done. Then the interview was conducted at the convenient places of farmers, such as their home, field, and their store. And the interview was conducted in an interpersonal way of communication. The raw data was recorded and stored in mWater application. Data were coded, tabulated, and analyzed using both descriptive and inferential statistics. Descriptive tools, such as frequency and percentage, were employed to examine respondents' socio-economic characteristics (age, gender, religion, ethnicity, and education). Additionally, a Chi-square test was used to determine the relationships between dependent and independent variables. The gathered information was entered and analysed by using tools like Word, excel, and *IBM SPSS Statistics V21.0*.

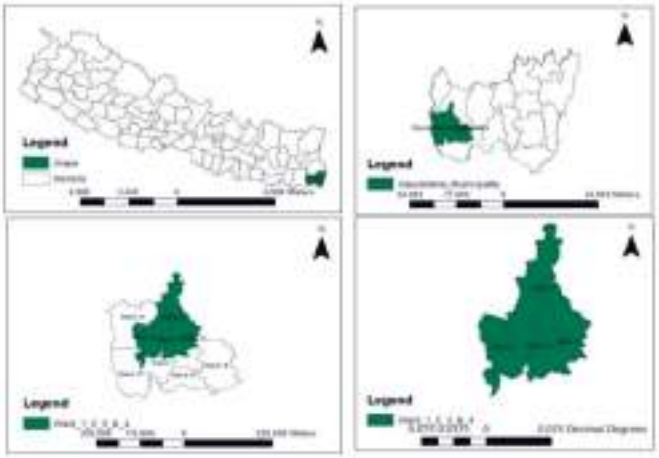


Figure 1. Administrative map of Gauradaha municipality, ward number 1,2,3 and 4

RESULTS

Farm machinery used, subsidy and ranking of farm machines

Importance of machineries

Findings of the study reveal that 43% of farmers used farm machineries to increase production, productivity, and profitability; 36% farmers used it to minimize human labor, and 21% for the timeliness of operation (Figure 2).

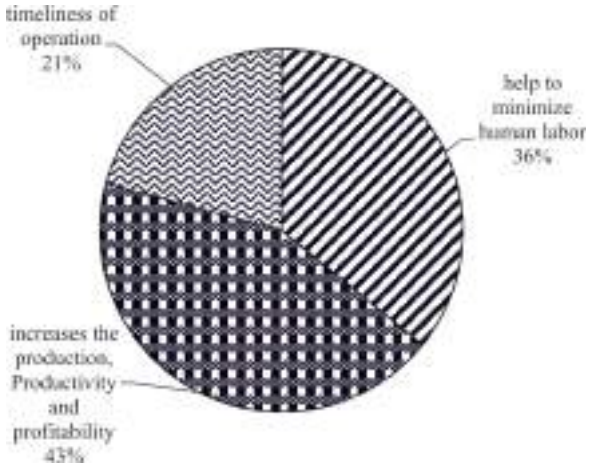


Figure 2. Importance of Machineries

Use of different farm machineries

Cultivator and thresher were most popular used by 100% of respondents while, 79.17% used pump sets or motor for watering the field, 55% used combine harvester, 42.5% used reaper for harvesting paddy and 11.7% used other types of machinery which include corn sheller, corn harvester, power tiller, driller and paddy straw cutter.

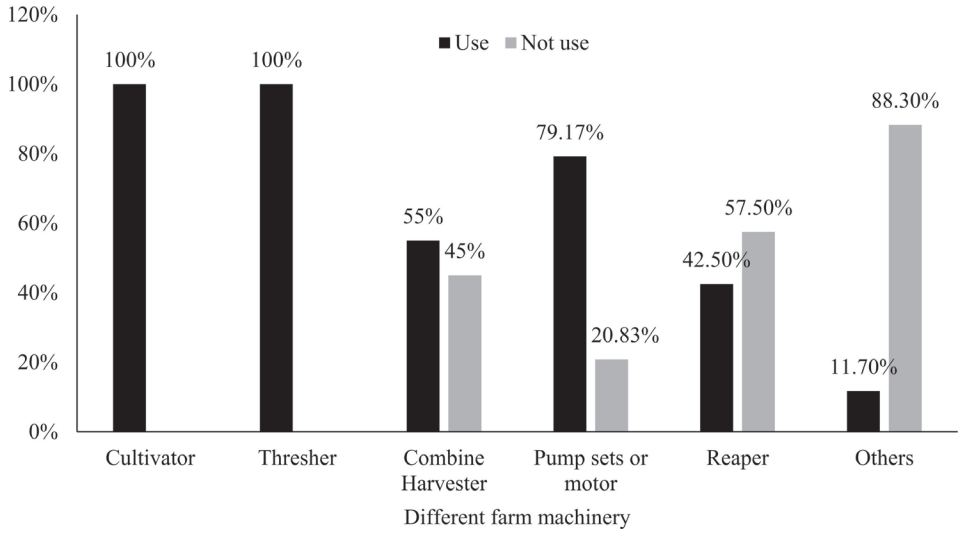


Figure 3. Use of different farm machinery

Machines availability

Around 96% of farmers opted to rent machinery for their agricultural operations. Only 3.33% purchased machinery independently, and a mere 0.83% received partial funding from government subsidies (Figure 4). This highlights a critical gap in governmental support for the adoption of farm machinery, which remains in its early stages.

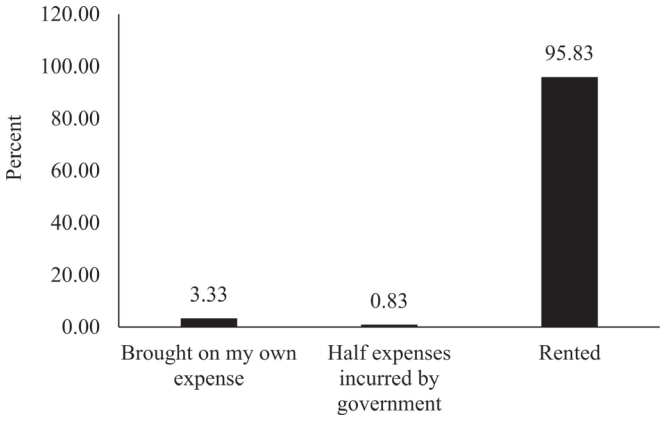


Figure 4. Machines availability

Subsidy to buy new machines

Findings of the study reveal that government subsidy reached only 10% of farmers to buy farm machinery as shown in Figure 5. High initial cost is reported as one major hinderance in adoption of farm machinery. And without subsidy, farmers in general are simply not capable of owing or renting on higher cost.

Subsidy provision

Among the 10% farmers who received subsidy 10% farmers received from their own municipality (local government) only about one percentage farmer received it from cooperatives (Table 1). 50% subsidy was provided to farmers for the purchase of machinery such as pump sets, Power tiller, driller etc. Majority of farmers received subsidy for the purchase of pump sets.



Figure 5. Subsidy received for machine purchase
Source: Field survey, 2024

Table 1. Provision of 50% subsidy

Category	Percent
Cooperatives	1%
Municipality	9 %

Source: Field survey, 2024

Rank of machineries

The survey results highlight the cultivator and thresher as the most essential tools, ranked by over 98% of respondents. The Cultivator is the top preference, with 55.46% ranking it first, while the Thresher's utility is distributed more evenly across the second to fourth positions. The combine harvester (ranked by 55%) also shows strong primary importance, with over half of its users (51.51%) placing it in the top spot. In contrast, pump sets (48.33%) and reapers (42.5%) are primarily viewed as secondary or tertiary tools. The motor (15%) and "Others" (13.33%) saw the lowest engagement, with the latter almost exclusively relegated to the fifth position or lower (Table 2).

Table 2. Rank of different machineries

Types of Machines	Ranking					Total	Overall
	1	2	3	4	5 or more		Rank
Combine Harvester	51.51%	19.69%	27.27%	0%	1.51%	55%	III
Cultivator	55.46%	32.77%	9.24%	4.20%	1.68%	98.17%	I
Motor	5.55%	0%	38.88%	38.88%	16.66%	15%	VI
Pump sets	24%	31%	1.72%	32.75%	10.34%	48.33%	IV
Thresher	5.08%	30.5%	27.11%	28.81%	8.47%	98.33%	II
Reaper	1.96%	55%	37.25%	17.64%	17,64%	42.5%	V
Others	0%	0%	0%	12.5%	87.5%	13.33%	VII

Source: Field survey, 2024

Farm mechanization and its relation to farm size, land holding, income

Relationship between farm mechanization with farm size and duration

The correlation analysis reveals a positive relationship between mechanization year, farm size, and technology adoption, with stronger effects observed as duration and size increase as shown in Table 3. While the early years of mechanization (1–5 years) showed a non-significant correlation (r = 0.39), prolonged engagement of more than five years resulted in a strong and highly significant positive association with technology adoption (r = 0.67**, p < 0.01). Furthermore, farm size significantly influenced adoption patterns; although both smallholders (< 0.3 ha) and commercial farmers (> 1 ha) exhibited significant positive correlations, the strength of the relationship was notably higher for commercial operations (r = 0.61*, p < 0.05) compared to small-scale farms (r = 0.34, p < 0.05).

Table 3. Pearson correlation between mechanization duration and farm size to mechanization

Mechanization year	(Pearson correlation r)
1-5 years	0.09 ns
>5yrs	0.67**
Small farmers (< 0.3 ha)	0.34*
Commercial farmers (>1 ha)	0.61*

*,** significant at 0.05 and 0.01 level of significance

Factors affecting adoption of Farm mechanization

Chi- square test was used for association between categories of land and different machines used in agriculture at 5% level of significance. There was significant association between land holdings and combine harvester (i.e., p-value= 0.000<0.05), there was significant association between land holdings and pump sets/motor (i.e., p-value=0.000<0.05) as shown in Table 4. There was insignificant difference between land holdings and Reaper (i.e., p-value=0.252>0.05). There was significant difference between land holdings and other types of machineries such as power tiller, driller, corn harvester, corn sheller etc. The larger the land of farmers of any level, the chances of adopting and using different machinery seem to prosper. So, size of land holding was found to have significant over use of different farm machineries.

Table 4. Relation between total cultivated land and use of farm machinery

Different Machineries	p-value
Combine Harvester	0.000
Pump sets or motor	0.000
Reaper	0.252
Others	0.020

Source: Field survey, 2024

Chi-square test was used for association between Annual Income and different machines used in agriculture at 5% level of significance. There was insignificant association between annual income and combine harvester (i.e., 0.58>0.05) as shown in Table 5. There was insignificant association between annual income and pump sets /motor (i.e., 0.640>0.05). There was significant association between annual income and reaper (i.e., 0.000<0.05) again there was insignificant association between annual income and other types of machineries such as power tiller, driller, corn sheller, corn harvester (i.e., 0.447>0.05).

Low-income farmers cannot afford a custom hiring centre. Survey results revealed that low and medium income is a non-significant association with custom hiring, as shown in table 6). Despite the Custom Hiring Centre rendering services at a fair price, our farmers are too poor to afford those. This clearly indicates that our farmers simply cannot afford the cost rates of machineries. positive correlation (r = 0.44*) indicates that the use of custom hiring centres is primarily affordable for commercialised farmers.

Problems of mechanization

Research shows that 32% of farmers reported maintenance and repair cost of machine is the primary obstacle to adopting farm mechanization, 26% noting high initial costs and lack of technical knowledge, 14% referencing inadequate infrastructure, and 2% concerned about frequent maintenance and repair challenges (Table 7).

Farmers perception

Cost of machines

Among farmers, a significant 59.17% feel that rental costs are too high, while 40.83% believe they are quite reasonable as shown in Table 8. Most farmers, 65%, get information about agricultural machinery from family and friends. Meanwhile, 19.17% rely on

Table 5. Relation between annual income and use of farm machinery

Different machineries	Status	2-5 lakhs	5-10 lakhs	<2 lakhs	>10 lakhs	P-Value
Combine harvester	Yes	19.7%	36.4%	3%	40.9%	0.58
	No	27.8%	35.2%	13%	24.1%	
Pump sets/Motor	Yes	21.1%	36.8%	8.4%	33.7%	0.640
	No	32%	32%	4%	32%	
Reaper	Yes	13.7%	39.2%	0%	47.1%	0.000
	No	30.4%	33.3%	13%	23.2%	
Others	Yes	21.4%	35.7%	0%	42.9%	0.447
	No	23.6%	35.8%	8.5%	32.1%	

Source: Field survey, 2024

Table 6. Relation between the annual income of farmers and their access to the custom hiring centre

Annual income	Pearson correlation (r)
Low income (less than 5 lakh)	0.09 ns
Medium income (5-10 Lakh)	0.29 ns
High income (> 10 lakh)	0.44*

ns=non-significant, * significant at 5 * level

Table 7. Major problems in the adoption of farm mechanization

	Percent	Rank
Frequent maintenance and repair	32%	I
High initial cost	26%	II
Lack of infrastructure	14%	IV
Lack of technical knowledge	26%	III
Others	2%	V

Table 8. Farmers perception towards cost of machines

Variable	Category	Percent
Do you think rental cost is high?	No	40.83
	Yes	59.17
Where do you get the information about machineries?	Agri-vet	19.17
	Family/Friends	65
	Neighbors	15
	Social media	0.83
Are the machines easily available to purchase?	No	25
	Yes	75
What is your opinion in the price of machineries?	Moderately expensive	45.83
	Very expensive	54.17

Source: Field survey, 2024

Agri-vets, 15% consult neighbors, and just 0.85% use social media. 75%of respondents believe that agricultural machines are easily accessible, while 25% think they are not.65% of farmers consider the price of machinery to be very expensive, while 55% view it as moderately expensive.

Mechanization impact

Research shows that 75% of farmers experienced a significant increase in productivity, while 23.33% saw moderate improvements (Table 9). However, 1.67% reported no change in their productivity. Kandel et al. (2021) reported that the implementation of farm mechanisation has a positive impact on maize production and productivity. According to a survey, farm mechanisation

Table 9. Farmers' perception of the impact of mechanization

	Category	Percent
Mechanization on Productivity	Significantly increased	75.00
	Moderately increased	23.33
	No change	1.67
Mechanization on labor requirements	Reduced labor significantly	64.17
	Reduced laborModerately	35.00
	No change	0.83
Mechanization on income	Significantly increased	75.83
	Moderately increased	23.33
	No change	0.83
Is mechanization essential for future farming in Nepal?	Strongly agree	66.67
	Agree	32.50
	Neutral	0.83

Source: Field survey, 2024

significantly reduces labor for 64.17%, while 42% see a moderate reduction. In contrast, only 0.83% believe there is no effect on labor requirements.75.83% of farmers experienced a significant boost in income, while 23.33% saw a moderate increase. Only 0.3% reported no change in their income. 66.67% of farmers strongly affirm that mechanisation is crucial for the future of farming in our country, while 32.5% agree. In contrast, just 0.83% feel that mechanisation has no role to play.

DISCUSSION

In Nepal, the majority of farmers are small-scale holders working on highly fragmented land. This fragmentation serves as a significant barrier to farm mechanization. Consequently, many farmers still rely on traditional hand tools such as spades, khurpis, and sickles, or small-scale equipment like MB ploughs and mini-tractors. According to Takeshima & Liu (2020), farm sizes smaller than 0.5 hectares significantly lower the adoption rate of modern machinery. In the Terai and other plain regions, the use of modern machinery including tractors for tillage and various harvesters is becoming essential. Farmers' most preferred farm operation for mechanization were irrigation, milling, plant protection, threshing and land preparation (Baruah et al., 2025). Due to the high labour demands of cultivation and harvesting, the cultivator and thresher have become the most common and popular machines among all farmers (Kandel et al., 2021; Ranabhat et al., 2025). Butter et al. (2025) also reported that majority of farmers preferred farm mechanization because of high labour cost. The threshing operations

trend can be linked to the limited availability of labour, coupled with higher labour wages, encouraging farmers to opt for tractor-mounted threshers. These machines are not only cost-effective but also reduce drudgery and save time compared to manual threshing or the use of draught animals (Raina et al., 2021).

Because of the high costs associated with purchasing equipment, most farmers prefer to rent machinery rather than own it (Ranabhat et al., 2025). Cooperatives play a vital role in this ecosystem by facilitating machine rentals, which directly increases the adoption of farm technology (Atinafu et al., 2022). To further encourage mechanization, cooperatives, Agriculture Service Centres, and other organizations provide critical support. Research by Atinafu et al. (2022) and Dhakal et al. (2024) highlights that partial or full subsidies provided by the government and farmer groups are essential for the successful adoption and purchase of new agricultural machinery which are accordance to our findings.

CONCLUSION

Farm mechanization is well adopted for tillage as well as harvesting. Cultivator and thresher were used by 100% of respondents. Likewise, most farmers used water pumps or motors, combine harvesters, reapers, and other machinery such as power tillers, drillers, corn shellers, corn harvesters, and paddy straw cutters respectively. Land holdings present a significant challenge for local farmers; 41.67% possess less than 10 kattha of land, a constraint that hinders their capacity to utilize machinery effectively. Around 96% of farmers opted to rent machinery for their agricultural operations. Survey revealed that only 10% of farmers received government subsidies to invest in machinery. High initial costs are a major barrier to adopting modern equipment. Without sufficient subsidies, many farmers struggle to afford to buy or rent the machinery they need. This highlights the need for greater government support and resources to help farmers embrace mechanization.

DECLARATIONS

Ethics approval and informed consent: Ethical approval was not required for this study. All authors concur with the submission, and informed consent was sought and received from all respondents

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The author declares that they have thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Article

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Social Life Cycle Assessment of Irrigation Technologies in Indian Cassava Farming

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HIGHLIGHTS

- Solar irrigation farmers achieved higher social sustainability scores than electricity irrigation farmers. Renewable irrigation technology promoted inclusive and sustainable cassava farming system.
- Community participation, labour welfare, and capacity building improved significantly under solar irrigation.
- Seven principal components explained 79.42% of total social sustainability variation.

ARTICLE INFO

Keywords: Social life cycle assessment, Solar irrigation, Cassava cultivation, Social sustainability, Renewable energy.

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ABSTRACT

Sustainable irrigation technologies play a vital role in improving rural livelihoods and strengthening social sustainability in agriculture. The present study assessed the social sustainability performance of cassava production systems under solar-powered and electric irrigation technologies in Kallakurichi district of Tamil Nadu, India, during 2025. A Social Life Cycle Assessment (SLCA) framework integrated with Principal Component Analysis (PCA) was employed to evaluate seven social dimensions, namely labour availability, labour welfare, women participation, capacity building, household welfare, community participation, and post-harvest participation. Primary data were collected from 640 cassava farmers using a structured interview schedule. The Kaiser–Meyer–Olkin value (0.853) and Bartlett's test of sphericity ($p < 0.001$) confirmed the suitability of the data for factor analysis. Seven principal components explained 79.42 per cent of the total variance. The findings revealed that farmers adopting solar irrigation achieved higher social sustainability scores than electric irrigation farmers across all dimensions. Greater improvements were observed in labour welfare, community participation, and capacity building. The composite SLCA index was higher for solar irrigation farmers (0.65) compared to electric irrigation farmers (0.50). The study concluded that renewable irrigation technologies promoted social sustainability, farmer welfare, and inclusive rural development in cassava production systems.

INTRODUCTION

Cassava (*Manihot esculenta* Crantz) was an important tropical tuber crop cultivated widely in Asia, Africa, and Latin America because of its adaptability to diverse agro-climatic conditions and its contribution to food security, agro-industrial development, and rural livelihoods (Pretty et al., 2018; Zhu et al., 2023). In India, cassava cultivation was concentrated mainly in southern states such as Tamil Nadu, Kerala, and Andhra Pradesh, where favourable climatic conditions supported commercial production.

Agricultural sustainability included economic, environmental, and social dimensions. Social sustainability focused on equity, labour welfare, participation, and community well-being, which influenced technology adoption, livelihood security, and long-term

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sustainable agricultural development (Eizenberg & Jabareen, 2017; Pal et al., 2017). Social factors such as education, extension contact, institutional credit, and market accessibility significantly influenced farmers' adoption of improved technologies and livelihood outcomes. Yadav et al. (2026) identified landholding size, education, extension contact, and credit access as important socio-economic determinants influencing sustainable agricultural development and farmer welfare in Punjab.

Social Life Cycle Assessment (S-LCA) emerged as a framework for evaluating the social and socio-economic implications of agricultural production systems. Unlike conventional Life Cycle Assessment (LCA), which primarily concentrated on environmental impacts, Social Life Cycle Assessment (S-LCA) was employed to evaluate the social and socio-economic impacts of production systems on various stakeholder groups, including workers, farm owners, local communities, and value chain actors. The assessment considered indicators related to labour conditions, occupational health and safety, employment opportunities, social benefits, community engagement, technology transfer, food security, and stakeholder welfare throughout the product life cycle (Mulyasari et al., 2023). Principal Component Analysis (PCA) was increasingly applied in sustainability studies to identify major dimensions influencing social sustainability outcomes.

Irrigation technologies played an important role in determining agricultural productivity. Conventional electric irrigation systems often faced challenges such as unreliable power supply, increasing operational costs, and groundwater depletion. Renewable energy-based irrigation technologies, particularly solar-powered irrigation systems, gained increasing attention as sustainable alternatives because they provide daytime irrigation and improved irrigation efficiency. Upreti et al. (2023) reported that solar-powered tubewells reduced irrigation costs and improved farm efficiency in Rajasthan. Similarly, Peer et al. (2026) observed that solar-powered irrigation systems improved crop yield, crop quality, crop diversification, and plant development among farming households in the Kashmir Valley. Kaur and Sharma (2022) also emphasized that improved irrigation scheduling methods enhanced water-use efficiency and promoted sustainable agricultural production systems in north-western India.

Despite the increasing adoption of renewable irrigation technologies, limited empirical evidence was available regarding their social sustainability implications in cassava production systems. Most previous studies mainly focused on productivity enhancement and environmental efficiency, while comparatively less attention was given to labour welfare, women participation, household welfare, and community engagement. Therefore, the present study evaluated the social sustainability performance of cassava production systems under solar-powered and electric irrigation technologies in Kallakurichi district of Tamil Nadu using a Social Life Cycle Assessment framework integrated with Principal Component Analysis.

METHODOLOGY

The study was conducted in Kallakurichi district of Tamil Nadu, India, one of the major cassava-producing regions in the state. The district was selected because cassava cultivation is closely associated with starch and sago processing industries, which provide employment opportunities and support rural livelihoods. Primary data were collected during the 2025 agricultural year using a multistage sampling design. Major cassava-growing blocks and villages were identified based on the extent of cassava cultivation, and farmers were randomly selected from the identified villages. A total of 640 cassava farmers were surveyed, including 320 farmers using solar-powered drip irrigation systems and 320 farmers using conventional electric drip irrigation systems.

Primary data were collected through structured face-to-face interviews using a pre-tested interview schedule. Information related to labour availability, labour welfare, women participation, capacity building, household welfare, community participation, and post-harvest participation was collected from the respondents. All indicators were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The selection of indicators was guided by the UNEP/SETAC guidelines for Social Life Cycle Assessment and previous sustainability studies related to agricultural sustainability assessment. The social sustainability indicators were selected based on the UNEP/SETAC Guidelines for Social Life Cycle Assessment and relevant agricultural sustainability literature. The suitability of the selected indicators was further verified through expert consultation, while their reliability and construct validity were assessed using Cronbach's alpha reliability analysis and Principal Component Analysis (PCA), respectively.

Before conducting the analysis, the reliability of the selected indicators was examined using Cronbach's alpha reliability analysis. The overall Cronbach's alpha value of 0.89 indicated a high level of internal consistency among the indicators. The collected indicator values were then standardized using the Z-score transformation method to remove scale differences among variables. The standardized value was calculated as:

$$Z_i = \frac{X_i - \overline{X}}{SD}$$

where Z_i represents the standardized value of indicator i, X_i denotes the original indicator value, $\overline{X}$ represents the mean value of the indicator, and SD denotes the standard deviation. Principal Component Analysis (PCA) was subsequently applied to identify dominant social sustainability dimensions and derive indicator weights. Components with eigenvalues greater than one were retained according to the Kaiser criterion, and Varimax orthogonal rotation was applied to improve interpretability. Principal Component Analysis (PCA) was conducted on the individual social sustainability indicators rather than on aggregated dimensions to identify the underlying factor structure and derive objective indicator weights. The complete rotated component matrix obtained through Varimax rotation is presented in Table 3.

The indicator weights were derived using factor loadings and eigenvalues obtained from PCA according to the following equation:

$$w_i = \frac{L_i \times E_j}{\Sigma(L_i \times E_j)}$$

PCA-derived weights were used to ensure an objective and data-driven assessment of indicator importance. Unlike equal-weighting approaches, this method assigns greater importance to

indicators that contribute more substantially to the explained variance of social sustainability dimensions, thereby reducing subjectivity and improving the robustness of the composite SLCA index.

where w_i represents the weight assigned to indicator *i*, *Li* denotes the factor loading, and E_j represents the eigenvalue of component *j*. The indicator values were normalized using the min–max normalization method:

$$N_i = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

Dimension indices were calculated using:

$$DI_d = \frac{1}{n_d} \sum_{i=1}^{n_d} N_i$$

Finally, the Social Life Cycle Assessment (SLCA) index was constructed using weighted aggregation:

$$SLCA = \sum_{i=1}^{n} w_i N_i$$

The resulting SLCA index was used to compare the social sustainability performance of cassava farmers adopting solar-powered and electric drip irrigation systems.

RESULTS

Social sustainability dimensions and principal component analysis

Table 1 The comparison of socio-economic characteristics revealed that farmers adopting solar-powered irrigation systems generally possessed stronger socio-economic profiles than those using electric irrigation systems. Solar irrigation farmers exhibited relatively better educational attainment, greater farming experience, higher involvement in cassava cultivation, larger landholding patterns, and improved income levels, indicating a stronger capacity to adopt and manage advanced agricultural technologies. Differences were also observed in occupational status, suggesting that solar irrigation adopters had comparatively better access to productive resources and livelihood opportunities. In contrast, family size, cropping pattern, and gender composition showed only minor variations between the two groups, indicating a broadly similar demographic structure. Overall, the findings suggest that favourable socio-economic conditions may have supported the adoption of renewable irrigation technologies among cassava farmers.

The assessment of social sustainability dimensions further demonstrated that solar irrigation farmers consistently outperformed electric irrigation farmers across all indicators. Higher levels of labour availability, labour welfare, women's participation, capacity building, household welfare, community participation, and post-harvest participation were observed among solar irrigation adopters. Stronger performance in community participation and capacity building reflected greater engagement with farmer organizations, training programmes, and institutional support systems, while improved labour welfare and women's participation indicated more inclusive and supportive farming environments. Although household welfare remained comparatively weaker than other dimensions, solar irrigation farmers still achieved better outcomes than their electric irrigation counterparts. These findings highlight that solar-powered irrigation systems contributed not only to improved farm operations but also to enhanced social sustainability, institutional engagement, and livelihood resilience within cassava production systems.

Table 1. Socio-economic characteristics of sample farmers and descriptive statistics of social sustainability dimensions

Characters	Solar Irrigation Farmers	Electric Irrigation Farmers	t-value	Confidence Interval	Effect Size
Age	1.83	2.05	-4.04	-0.22	-0.52
Educational Status	3.70	2.73	12.28	0.97	1.59
Experience in Farming	2.23	2.02	4.04	0.22	0.52
Farming Experience in Cassava	2.00	1.88	2.79	0.12	0.36
Gender	1.35	1.27	2.32	0.08	0.30
Family Size	1.87	1.93	-2.05	-0.07	-0.27
Occupation	1.77	1.63	3.01	0.13	0.39
Land Holding Patterns	2.20	2.00	3.84	0.20	0.50
Cropping Patterns	2.50	2.53	-0.53	-0.03	-0.07
Annual Income	2.07	1.83	4.24	0.23	0.55

Dimension-wise Descriptive Statistics of Social Sustainability Indicators

Dimension	Solar Irrigation (Mean)	Electric Irrigation (Mean)
Labour availability	3.58	2.98
Labour welfare	3.60	3.00
Women participation	3.57	2.97
Capacity building	3.60	3.04
Household welfare	3.55	2.93
Community participation	3.69	3.06
Post-harvest participation	3.59	2.98

Note: Higher mean values indicate relatively better socio-economic status and stronger social sustainability performance among cassava farmers. Effect size values represent the magnitude of differences between solar and electric irrigation farmer groups.

The Kaiser–Meyer–Olkin (KMO) statistic indicated a high level of sampling adequacy, confirming that the data were suitable for factor analysis. Furthermore, Bartlett's Test of Sphericity was significant, demonstrating the presence of sufficient correlations among the variables to justify the application of PCA. The significant Bartlett's test confirmed that the selected indicators were sufficiently correlated for dimensional reduction. These findings demonstrated that the dataset was appropriate for extracting principal components and constructing a reliable composite sustainability index.

The Principal Component Analysis (PCA) results presented in Table 2 supported the retention of seven components based on the Kaiser criterion, whereby components with eigenvalues greater than one were considered significant. Prior to extraction, the suitability of the dataset for PCA was confirmed through KMO and Bartlett's tests, indicating adequate intercorrelations among variables. The retained components collectively explained a substantial proportion of the total variance, suggesting that the extracted factor structure adequately represented the underlying dimensions of social sustainability. The first two components accounted for the largest share of variance, while the remaining components contributed additional explanatory information and captured distinct aspects of the social sustainability framework. The retention of seven components was further supported by their conceptual relevance and strong factor loadings, which facilitated meaningful interpretation of the identified dimensions and ensured comprehensive representation of the social indicators included in the analysis.

The rotated component matrix presented in Table 3 revealed a clear clustering of indicators into seven distinct social sustainability dimensions. The strong association between indicators their respective components confirmed the conceptual validity of the selected dimensions. The extracted dimensions represented women participation, labour welfare, labour availability, capacity building, household welfare, community participation, and post-harvest participation.

Social sustainability performance of cassava farmers

The dimension-wise SLCA scores presented in Table 4 showed that solar irrigation farmers achieved higher sustainability values across all seven dimensions compared with electric irrigation farmers. Community participation emerged as the highest-performing dimension under solar irrigation systems, followed by labour welfare and capacity building. Women participation recorded higher values under solar irrigation systems compared with electric irrigation systems. Labour availability recorded higher values under solar irrigation systems than under electric irrigation systems. Household welfare recorded the lowest sustainability scores under both irrigation systems.

Farmers using solar irrigation systems achieved a higher average SLCA score, whereas electric irrigation farmers recorded a comparatively lower score. The variation observed between the two irrigation systems was statistically significant at the 1% level, as evidenced by the independent sample t-test results presented in Table 5. The results indicated that renewable irrigation technologies contributed positively toward improved labour organization, institutional participation, and overall social sustainability outcomes within cassava production systems.

Sustainability classification and distribution of farmers

The distribution of farmer-level SLCA scores was examined boxplot visualization in Figure 1. Solar irrigation farmers recorded

Table 2. Total Variance Explained by Principal Components

Principal Component	Eigenvalue	Variance Explained (%)	Cumulative Variance (%)
1	4.286	14.29	14.29
2	4.112	13.71	27.99
3	3.798	12.66	40.66
4	3.339	11.13	51.78
5	3.189	10.63	62.41
6	2.705	9.02	71.43
7	2.396	7.99	79.42

Note: Seven components with eigenvalues above one explained 79.42% variance, indicating strong representation of social sustainability indicators.

Table 4. Dimension-wise Social Life Cycle Assessment under Solar and Electric Irrigation

Social Sustainability Dimension	Solar Irrigation	Electric Irrigation	Difference
Labour availability	0.65	0.50	+0.15
Labour welfare	0.66	0.51	+0.15
Women participation	0.64	0.48	+0.16
Capacity building	0.66	0.51	+0.15
Household welfare	0.48	0.37	+0.11
Community participation	0.68	0.53	+0.15
Post-harvest participation	0.64	0.49	+0.15

Note: Index values range from 0 to 1, where higher values indicate stronger social sustainability performance under irrigation systems.

Table 3. Rotated Component Matrix of Social Sustainability Indicators (Varimax Rotation)

Principal Component	Indicators	Factor Loading Range	Identified Dimension
Component 1	W11–W15	0.879 – 0.902	Women participation and gender equity
Component 2	LW6–LW10	0.872 – 0.910	Labour welfare and working conditions
Component 3	L1–L5	0.882 – 0.891	Labour availability and employment
Component 4	CB16–CB19	0.892 – 0.907	Capacity building and knowledge access
Component 5	FH20–FH23	0.870 – 0.894	Farm household welfare
Component 6	CP24–CP27	0.860 – 0.885	Community participation and institutional support
Component 7	PH28–PH30	0.894 – 0.905	Post-harvest and market participation

Note: For better interpretation, only factor loadings above 0.70 are presented, and Varimax rotation was applied during analysis.

Table 5. Independent Sample t-test for Comparison of SLCA Scores

Variable	Mean SLCA Score	t-value	p-value
Solar irrigation farmers	0.65	12.4	< 0.01
Electric irrigation farmers	0.50		

Note: Independent sample t-test results confirmed a significant difference ($p < 0.01$), indicating superior social sustainability among solar irrigation farmers.

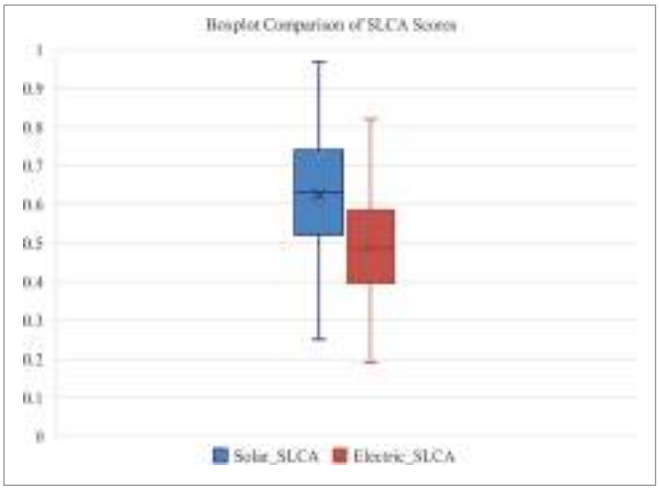


Figure 1. Boxplot Comparison of SLCA Scores by irrigation type

a broad range of SLCA scores, with most observations concentrated at relatively higher sustainability levels. In contrast, electric irrigation farmers recorded comparatively lower sustainability values, with the majority of observations concentrated within the moderate sustainability category. The higher median and upper quartile values observed under solar irrigation systems indicated broader improvements in labour welfare, institutional participation, and livelihood resilience among solar irrigation adopters.

Farmers were categorized into low sustainability (SLCA < 0.40), moderate sustainability (0.40–0.60), and high sustainability (SLCA > 0.60) groups. Approximately 65 per cent of solar irrigation farmers belonged to the high sustainability category, while only 29 per cent of electric irrigation farmers achieved similar sustainability levels. In contrast, 22 per cent of electric irrigation farmers fell within the low sustainability category compared with only 6 per cent among solar irrigation farmers. These results demonstrated broader and more inclusive sustainability improvements under solar irrigation systems.

DISCUSSION

The study demonstrated that solar-powered irrigation systems enhanced the social sustainability of cassava production systems compared with conventional electric irrigation systems. The observed improvements extended beyond irrigation performance and reflected broader benefits for labour welfare, institutional participation, capacity building, and livelihood resilience. These findings suggested that renewable energy technologies can contribute to socially inclusive agricultural development by reducing operational constraints and improving farmers' access to resources and opportunities.

The superior social sustainability performance of solar irrigation farmers could largely be attributed to the reliability and flexibility of solar-powered irrigation systems. Consistent access to irrigation enabled farmers to undertake agricultural operations according to crop requirements rather than being constrained by irregular electricity supply. Improved scheduling of farm activities likely strengthened labour management, reduced production uncertainties, and enhanced overall farm efficiency. Similar findings were reported by Siririka et al. (2025), who found that renewable irrigation technologies strengthened socio-economic sustainability and supported rural agricultural development.

Community participation emerged as a key contributor to social sustainability among solar irrigation farmers. Greater involvement in farmer organizations, extension programmes, and collective activities indicated stronger social networks and institutional linkages. Such interactions facilitate knowledge exchange, improve access to information, and encourage collective problem-solving among farming communities. Okolie et al. (2024) similarly reported that farmer networks and institutional participation enhanced resilience and promoted the adoption of sustainable agricultural innovations. The findings therefore highlighted the importance of strengthening community-based institutions alongside technological interventions.

The results also suggested that solar irrigation technologies indirectly promoted capacity building through increased interaction with extension services and training programmes. Access to technical information and advisory support enhanced farmers' understanding of irrigation management and sustainable production practices. Naveen et al. (2024) reported that extension support improved farmers' adaptive capacity and facilitated the adoption of improved technologies. This indicated that the benefits of renewable irrigation technologies extended beyond physical infrastructure to include improvements in human capital and knowledge systems.

Labour-related dimensions also showed notable improvements under solar irrigation systems. Reliable irrigation reduced interruptions in farm operations and enabled more efficient allocation of labour resources throughout the production cycle. Improved working conditions and operational efficiency may have contributed to greater labour stability and welfare. Verma et al. (2020) similarly observed that renewable energy-based irrigation systems improved labour productivity and farm management efficiency. These findings emphasized the potential of solar irrigation technologies to support employment-related aspects of agricultural sustainability.

Women participation was another dimension positively influenced by solar irrigation adoption. Reduced irrigation constraints and improved operational flexibility may have created greater opportunities for women to engage in agricultural activities and farm-level decision-making. Quisumbing et al. (2014) reported that gender-inclusive agricultural systems strengthened household welfare and supported equitable rural development. The findings therefore underscored the importance of considering gender outcomes when evaluating the sustainability impacts of agricultural technologies.

The PCA results confirmed the suitability of the selected indicators for measuring social sustainability in cassava production systems. The strong factor structure demonstrated that the identified dimensions collectively captured the multidimensional nature of social sustainability. Similar PCA-based approaches were used by Sala et al. (2015) and Moldan et al. (2012) to evaluate sustainability performance across multiple dimensions. The integration of PCA with the SLCA framework therefore provided a robust methodological approach for sustainability assessment.

Despite the positive influence of solar irrigation technologies, household welfare remained a relatively weaker dimension. This finding suggested that technological improvements alone may not be sufficient to address broader socio-economic challenges affecting farming households. Factors such as market access, value-chain development, income stability, and financial support continue to play a critical role in shaping household welfare outcomes. Therefore, policy interventions should combine technological adoption with market and institutional support mechanisms to achieve more comprehensive sustainability improvements.

Overall, the findings highlighted that renewable irrigation technologies can contribute substantially to socially sustainable and resilient cassava production systems. By strengthening institutional engagement, labour welfare, capacity building, and gender participation, solar-powered irrigation systems supported broader rural development objectives and promoted inclusive agricultural sustainability.

Despite providing valuable insights into the social sustainability performance of cassava production systems, the study has certain limitations. The analysis was confined to selected cassava-growing areas of Kallakurichi district and may therefore be subject to selection bias, limiting the generalizability of the findings. In addition, the study relied on self-reported responses collected through farmer interviews, which may be influenced by recall errors or respondent perceptions. Furthermore, the cross-sectional nature of the study captured social sustainability conditions at a single point in time and did not account for temporal changes. Future studies employing longitudinal data and broader geographical coverage may provide a more comprehensive assessment of the long-term social sustainability implications of irrigation technologies.

CONCLUSION

The results indicated that farmers adopting solar-powered irrigation systems recorded higher social sustainability performance across key dimensions, including labour availability, labour welfare, women's participation, capacity building, community participation, household welfare, and post-harvest participation. The PCA results confirmed the suitability of the selected indicators and identified seven major dimensions that collectively represented the social sustainability structure of cassava farming systems. The findings suggest a positive association between solar irrigation adoption and improved social sustainability outcomes. From a policy perspective, promoting renewable energy-based irrigation technologies through targeted subsidies, affordable credit, extension support, and farmer training programmes may strengthen social well-being and livelihood resilience. Integrating social sustainability indicators into agricultural development programmes can further support evidence-based policymaking and contribute to inclusive and sustainable rural development.

DECLARATIONS

Ethics approval and informed consent: Throughout the study, the respondents were asked for their informed consent.

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Research Article

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Sustainable Growth: Enhancing Youth Livelihoods with Agricultural Financial Capital Enhancement Skills in Terai Region, West Bengal

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HIGHLIGHTS

- Risk-taking ability was the strongest positive predictor of financial capital generation through skill development among rural youth.
- Training exposure and attitude towards agriculture were negatively associated with financial capital generation through skill development.
- Psychologically-informed skill development program can strengthen financial capital and sustain rural youth livelihoods effectively.

ARTICLE INFO

Keywords: Financial capital, Rural youth, Sustainable livelihoods, Skill development and risk taking ability.

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ABSTRACT

Financial capital has been found as one of the important factors towards sustainability in the rural youth livelihoods, but research on how financial capital can be built through skills enhancement among the rural youth in India is limited. The study aimed to explore the effect of profile factors on skill development based financial capital generation among rural youths of Cooch Behar and Malda districts, West Bengal. A total of 200 farm youth were randomly sampled from 20 randomly selected villages from the four blocks. The data collected during 2025 were analysed with descriptive statistics, correlation analysis and multiple regression analysis. Eight factors such as annual income, annual expenditure, material possession, agricultural implement possession, land holding, risk taking ability, economic motivation and skill possessed were found to influence the financial capital generation through the skill development process positively and significantly whereas training exposure and attitude towards agriculture were negatively and significantly related to the dependent variable of the study. When using multiple regression analysis, the R^2 value is 0.324. The results indicate the need for targeted skill development training for adolescents to facilitate the development of financial capital and sustainable livelihoods in agriculture in rural communities.

INTRODUCTION

The agricultural sector contributes approximately 18% of India's GDP and employing around 54% of the country's total labour force (Department of Agriculture & Farmers Welfare, 2024). A serious crisis exists where youth are leaving the agriculture sector due to the lack of economic opportunities and social status of agriculture among the young minds (Uddin & Antriyandarti, 2025). The concepts like investment, budgeting, financial services, and others can be understood by the young agripreneurs so that they can maximize their productivity and profitability (Mohanty et al., 2025). Financial capital is one of the main assets in the Sustainable Livelihoods Framework (Chambers & Conway, 1992; DFID, 1999; Kyeyune & Ntayi, 2025) and it refers to the means by which

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people have access to income, credit, assets ownership, and access to formal financial institutions. A young farmer who produces crops but also manages their income and makes efficient investment choices in technology (Figurek et al., 2023), all-encompassing strategy can pave the way for sustainable development, lower the migration and unemployment rates of rural youth (Maurya et al., 2022) and enable young people to play a vital role in agricultural production (Geza et al., 2022). The aim is to develop a generation of Young Farmers who are financially literate and economically empowered (Joshi and Kashyap, 2024). Combining farming and financial education (Kurdys-Kujawska et al., 2025) can create an era of youth who can become both farmers and entrepreneurs (Chinchmalatpure & Tekale, 2019). With the advent of Artificial Intelligence (AI) in the recent times, the concept of smart farming and precision farming has been encouraged, thus making the agriculture more efficient, technologized and appealing to the rural youth (Singh et al., 2022). Agriculture is a key economic activity in many economies, especially in rural areas (Gulati & Juneja, 2022). To tap this potential, Agricultural Financial Capital Enhancement Skills was designed, which combines agricultural skills with financial knowledge (Kumar et al., 2022). The essence of agriculture sustainability is to satisfy the needs of the present generation without harming the needs of future generations (Soni et al., 2022; Sai et al., 2024; Kumari et al., 2024; Raman, 2024). Empowering youth in agriculture involves more than just technical skills. It comprises financial education, which is essential for resource management, obtaining credit facilities and making wise investment decisions (Tiwari et al., 2023; Vasanthi & Preethi, 2024). As the financial capital skills of the young agripreneurs improve, they can budget effectively (Kaur & Dharni, 2024). Young farmers adapt to both sustainable farming practices and financial management. This double expertise can revolutionize their life for economic stability and growth (Mishra et al., 2023). This will combine sustainable agricultural practices with the skills for financial capital enhancement to build a new generation of sustainable financially savvy young farmers (Ray et al., 2022).

METHODOLOGY

Two districts of Cooch Behar and Malda were selected for the study in West Bengal through purposive sampling as in both the districts, rural youth are actively involved in farming and are an important group in creating income and sustainability of livelihoods in the Terai agro-climatic region. The respondents were selected by using multistage random sampling methodology. Two blocks were randomly chosen from each district and two villages were selected from each block, randomly, resulting in selection of eight villages. From all selected villages, a list of all the farm youths in the age group of 18-35 years engaged. Twenty-five were randomly selected from each village, and thus the total respondent selected were 200 rural farm youth. Financial Capital Generation via Skill Development (Y), was decided based on the SLF model (Chambers & Conway, 1992; DFID, 1999). Evaluation of the financial capital generated by skill development of respondents was done using the validated composite scale. Twenty predictor variables have been identified and grouped into four types: socio-personal, socio-economic, socio-psychological and situational attributes. The rating systems used for each variable studied were well-designed, pretested with an established content validity scale and reliability (internal consistency). The main data for analysis was collected directly from respondents using the pre-tested face-to-face interview guide, which was tested in 20 respondents in the field outside the study location. The collected data were then statistically analyzed using descriptive measures like mean, standard deviation (S.D.) and coefficient of variation (C.V. = S.D. / Mean × 100). Each of the independent variables was correlated with the dependent variable with the use of bivariate correlation analysis using the Pearson product-moment correlation coefficient (r). To find the significant predictors of financial capital creation as well as R^2 coefficient of determination, multiple linear regression analysis was performed. The annual amount spent (X_6) and level of social interaction (X_{19}) were not considered in the regression model as they were found to be highly intercorrelated by means of Variance Inflation Factor (VIF). Thus, a total of 18 predictors were used in the model built. The unstandardized coefficients were examined for significance with $p \leq 0.05$ and $p \leq 0.01$. Standardized coefficients (beta) were used to facilitate comparisons between the relative contributions of predictors to the overall variance of Y.

RESULTS

Ninety percent of the respondents were in the age group of 25-34 years and 10% were below 25 years (Table 1). As for education 74% of the respondents were educated from secondary education, 14% were of the education level of primary education, and 12% received higher secondary education. Medium (78%), low (9%) and high (13%) family educational status. Among the socio-economic characteristics, 67% of the respondents had a medium level of farming experience, whereas 16.5% each belonged to the low and high categories. Similarly, the majority of respondents had medium annual income (65%), annual expenditure (65.5%), material possession (63%), agricultural implement possession (72%), and landholding (70.5%). The socio-psychological characteristics revealed that most respondents exhibited medium levels of independency (87%), risk-taking ability (90%), economic motivation (97.5%), orientation towards skill development (87%), attitude towards agricultural practices (79.5%), and knowledge acquired (88%), and skill acquired (89.5%). Likewise, the majority had medium levels of extension contact (78.5%), mass media exposure (69.5%), and training exposure, while 91% reported medium to high social participation. With respect to the dependent variable, financial capital generation through skill development was observed at a medium level among 88.5% of the respondents, whereas 8% and 3.5% belonged to the high and low categories, respectively.

The Pearson's coefficient of correlation between economic/ financial capital creation from skill development and 20 independent variables is shown in Table 2. Out of the Socio-demographic variables, none was significantly correlated with financial capital. Annual income (r = 0.294), annual expenditure (r = 0.333), material possession (r = 0.233), possession of agricultural implements (r = 0.200) and land ownership (r = 0.164) were positively and significantly correlated with the dependent variable. The highest positive correlation coefficient was found between risk taking capacity (r = 0.449) and economic motivation (r = 0.275) and skill

Table 1. Consistency of the variables selected for the study

Variables	Max.	Min.	Mean	S.D.	C.V. (%)
Socio-personal variables					
Age (X_1)	34	18	28.49	4.06	14.24
Education (X_2)	15	02	8.89	3.05	34.31
Farming Experience (X_3)	18	02	10.61	3.74	35.25
Family educational status (X_4)	06	02	3.79	0.72	18.20
Socio-economic variables					
Family annual income (X_5)	300	40	125.27	49.33	39.38
Family annual expenditure (X_6)	250	35	110.56	41.90	37.90
Material possession (X_7)	28	06	13.25	3.60	27.17
Agricultural implements possession (X_8)	30	08	14.85	4.17	28.08
Land holding (X_9)	4.40	0.73	2.24	0.80	35.71
Socio-psychological variables					
Independency (X_{10})	26	18	22.40	1.02	4.55
Risk taking Ability (X_{11})	27	19	24.80	1.36	5.48
Economic motivation (X_{12})	26	21	25.00	0.76	3.04
Youth orientation towards development of skill in Agriculture (X_{13})	44	38	41.00	1.07	2.61
Attitude about Agricultural Practices (X_{14})	87	74	79.74	1.81	2.27
Knowledge Acquired (X_{15})	18	13	15.48	0.74	4.78
Skill Acquired (X_{16})	18	13	15.47	0.72	4.65
Situational attributes					
Extension contact (X_{17})	15	09	11.56	0.89	7.70
Mass media exposure (X_{18})	11	05	8.42	1.09	12.95
Social participation (X_{19})	03	01	1.63	0.64	39.26
Training Exposure (X_{20})	12	04	6.11	1.34	21.93
Predicted Variable					
Financial Capital	20	15	18.84	0.65	3.45

Table 2. Correlation Coefficient of economic/ financial Capital generation through skill development with 20 causal variables

Variables	Coefficient of Correlation
Socio-personal	
Age (X_1)	-0.022
Education (X_2)	0.006
Farming experience (X_3)	-0.018
Family education status (X_4)	0.109
Socio-economic	
Annual income (X_5)	0.294**
Annual expenditure (X_6)	0.333**
Material possession (X_7)	0.233**
Agricultural implements possession (X_8)	0.200**
Land holding (X_9)	0.164*
Socio-psychological	
Independency (X_{10})	0.051
Risk ability (X_{11})	0.449**
Economic motivation (X_{12})	0.275**
Youth orientation towards skilldevelopment (X_{13})	0.122
Attitude about agricultural practices (X_{14})	-0.190**
Knowledge acquired (X_{15})	0.098
Skill acquired (X_{16})	0.171*
Situational attributes	
Extension contact (X_{17})	0.085
Mass media exposure (X_{18})	0.053
Social participation (X_{19})	-0.022
Training exposure (X_{20})	-0.236**

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

obtained (r = 0.171) in the socio-psychological variables. The attitude of agricultural practice (r = -0.190) and training experience (r = -0.236) showed negative and significant correlation coefficients. The other Socio-psychological variables like independency, youth inclination towards skill development, knowledge acquired, extension contacts, mass media contacts and social participation were not significantly correlated with financial capital creation.

The result of the Multiple Regression analysis between economic/financial capital generation and 18 predictor variables is shown in Table 3. Predictor variables like annual expenditure (X_6) and social participation (X_{19}) were omitted because of high multicollinearity among them. From the value of $R^2 = 0.324$, we can see that the set of 18 predictor variables accounted for 32.40% variation of the dependent variable. Of all the predictor variables used in the model, the most significant positive predictor variable is risk-taking ability (X_{11}) ($\beta = 0.435$, $t = 5.028$, $p < 0.01$). Training exposure (X_{20}) was found to be a significant negative predictor variable ($\beta = -0.249$, $t = -2.911$, $p < 0.01$).

DISCUSSION

The age group of 25-34 is the major age group which indicates the active farming population (Uddin & Antriyandarti, 2025). The majority of the respondents are secondary educated which is consistent with moderate financial literacy scores of the agripreneurs (Kaur & Dharni, 2024), whereas the small percentage of higher-educated youth supports the results of other studies that higher education not only fails to encourage young people to participate in agriculture, but also reduces their interest in doing so (Geza et

Table 3. Results of Multiple regression analysis of economic/ financial capital (Y_2) with 18 predictor variables

Variables	Unstandardized Coefficients		Standardized Coefficients	t-value
	B	Std. Error	Beta	
Socio-personal				
Age (X_1)	-.009	.025	-.055	-.349
Education (X_2)	-.027	.016	-.127	-1.712
Farming experience (X_3)	.002	.027	.011	.070
Family education status (X_4)	.045	.062	.050	.735
Socio-economic				
Annual income (X_5)	-.012	.013	-.089	-.899
Material possession (X_7)	.025	.014	.142	1.864
Agricultural implements possession (X_8)	.018	.011	.116	1.615
Land holding (X_9)	.063	.062	.079	1.024
Socio-psychological				
Independency (X_{10})	-.056	.045	-.089	-1.241
Risk ability (X_{11})	.206	.041	.435	5.028**
Economic motivation (X_{12})	.062	.065	.073	.953
Youth orientation towards skill development (X_{13})	-.003	.041	-.005	-.080
Attitude about agricultural practices (X_{14})	.051	.029	.142	1.748
Knowledge acquired (X_{15})	-.050	.097	-.058	-.521
Skill acquired (X_{16})	.165	.098	.185	1.678
Situational attributes				
Extension contact (X_{17})	.086	.054	.118	1.581
Mass media exposure (X_{18})	-.035	.044	-.058	-.795
Training exposure (X_{20})	-.120	.041	-.249	-2.911

R^2=0.324; * Significant at 5% level; ** Significant at 1% level

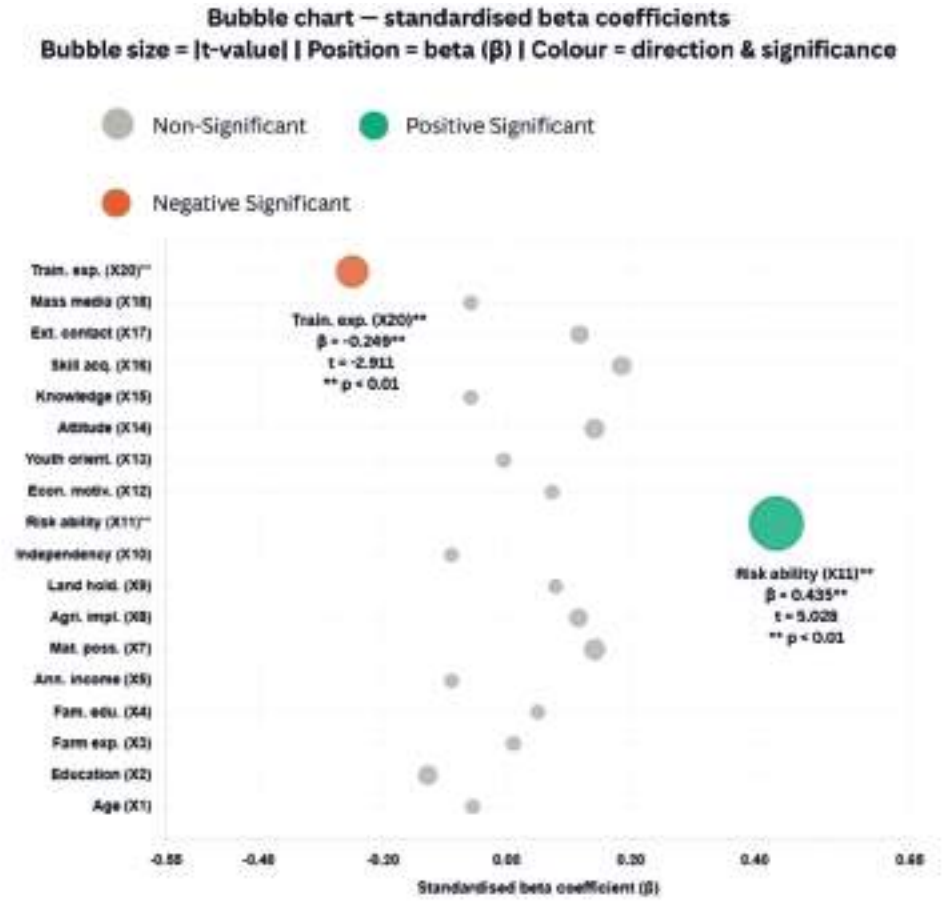


Figure 1. Bubble chart of multiple regression analysis of economic/ financial capital

al., 2022). 67% of respondents have moderate farming experience and are ready to invest in farming skills (Figurek et al., 2023). The overall medium socio-economic status expressed through income, expenditure, material possession and smallholder land holdings reveals that financial inclusion gaps have persisted as one of the main barriers for rural agricultural youth (Gulati & Juneja, 2022; Kumari et al., 2024).

The presence of high economic motivation (97.50%), risk-taking ability (90%), and youth focus on skill development (87%) implies significant but inadequately leveraged entrepreneurial talent among the participants, just as found by (Kyeyune & Ntayi, 2025). The relatively low level of attitudes towards agriculture (79.50%) and knowledge/skill acquisition (88% and 89.50%, respectively) reflects a potential that can be harnessed through targeted approaches such as need-based capacity building, practical skill development programmes, financial literacy initiatives and technology-oriented agricultural training among rural youth, as recommended by Raman, 2024 and Kurdys-Kujawska et al. (2025). Likewise, the moderate extension communication (78.50%) and mass media communication (69.50%) indicate a need to improve institutional communication, given that information is an important factor in the formation of financial capital (Chambers & Conway, 1992; DFID, 1999).

Socio-personal variables exhibited non-significant relation with the creation of financial capital, implying that socio-demographic indicators, when considered alone, are not adequate for creating skill-based capital. In case of socio-economic variables, a positive association was established between annual income, annual expenditure, material possessions, implement ownership, and land holdings, thereby implying that youth, who enjoy better economic endowments, find it easier to access financial organizations and skills development programs (Gulati and Juneja, 2022; Arunkumar et al., 2023; Kumari et al., 2024; Arunkumar et al., 2025). Risk taking ability (r=0.449), economic motivation (r=0.275) and skill acquired (r=0.171) emerged as significant socio-psychological variables (Soni et al., 2022; Kyeyune and Ntayi, 2025). Negative association between attitude towards farming and training exposure suggested that skill-based youth emphasize on capabilities rather than earnings (Figurek et al., 2023; Raman, 2024).

The regression explained 32.40% of the variance in financial capital generation, while the remaining part was explained by the factors that were not included in the regression model (social capital, institutional access and policy environment). Only two variables were found to be statistically significant. Risk-taking ability ($\hat{a}$ = 0.435, t = 5.028, $p < 0.01$) was the strongest positive predictor. Financial capital is enhanced through swifter and more risk-oriented youth engaging in agribusiness activities, the promotion of financial resources and capital involvement in skill development. This corroborates (Soni et al., 2022) on risk orientation and entrepreneurial engagement.

Training exposure ($\beta = -0.249$, t = –2.911, $p < 0.01$) actually had a negative significant association, suggesting that youth with higher levels of prior training perceived lower need for additional financial skill development, and already had established networks and knowledge. Some lack of synergy between multiple training programmes could also have resulted in confusion regarding the skills relevant to the learning outcome, which is in line with (Arunkumar et al., 2021; Figurek et al., 2023), who observed that lack of synergy between multiple training programmes hinders and demoralizes purposeful skill formation.

CONCLUSION

The study underscores the importance of the livelihood sustainability issue for young people in the remote areas, and the significance of the accessibility of financial resources and their use. Skill development, in terms of enhancing financial resources, is closely related to the development of sustainable livelihoods. The analysis reveals that the financial capital generation is in positive correlation with annual income, annual expenditure and material possession, possession of agricultural implements, land holding, risk taking ability, economic motivation and acquired skill. On the other hand, the financial capital generation is negatively correlated with training exposure and attitude towards agricultural practices. On the other, financial capital generation is inversely related to the training exposure and attitude towards agricultural practices. This study highlights the need for focused up-skilling programmes to promote financial capital and the livelihoods of rural youth in general.

DECLARATIONS

Ethics approval and informed consent: Ethical norms were strictly followed while conducting this research according to the principles of social science research. All participants provided their informed consent prior to the conduct of the research using personal interview method.

Conflict of interest: The authors have declared that no conflict of interest exists in the conduct of the research.

Authors' contribution: Biman Maity conducted the field investigation, data collection, statistical analysis. Kausik Pradhan supervised the study and contributed to research design and interpretation of results. Chigilipalli Mounika, Marimuthu Praveenkumar, Swapnamay Ghosh and Ajay Kumar Prusty assisted in literature review, data interpretation, manuscript preparation and editing. All authors read and approved the final manuscript.

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Construction and Validation of Instrument to Assess the Multifaceted Potential of School Vegetable Gardens

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HIGHLIGHTS

- Developed and standardized a 43-item Likert scale assessing multifaceted potential of school vegetable gardens across five dimensions.
- Items refined from 75 to 43 using relevancy (>80%) and t-value (>2.306) criteria with expert validation.
- Scale showed high reliability (Cronbach's α = 0.983), strong split-half reliability, and satisfactory convergent validity (AVE).

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ABSTRACT

The study is focused on developing and standardizing a scale to assess the multifaceted potential of school vegetable gardens as perceived by students. This instrumentation was carried out in the year 2025.The summated rating technique as proposed by Likert (1932) and refined by Edwards (1957) was employed for the construction of the instrument. Initially, a comprehensive literature analysis, conversations with subject matter experts, and field-level observations pertaining to school gardening programs produced a pool of 75 statements. After editing using standard criteria, 66 relevant statements were retained. Of these, 55 items were chosen based on a relevancy score of more than 80%. After item assessment, a total of forty three statements with t- values above 2.306 at the 5% level of threshold were incorporated and subjected to reliability and validity tests. Then, Factor Analysis (Exploratory) was carried out to confirm the dimensional structure and establish convergent validity. The final scale consisted of 43 items grouped under five dimensions: Economic, Environmental, Social, Governance, and Health & Well-being. The confirmed scale proved higher internal consistency with a Cronbach's value of 0.983 and satisfactory split-half reliability. Convergent validity was established by the Average Variance Extracted (AVE) values outstanding the threshold for each dimension.

INTRODUCTION

Education plays a crucial role in shaping socially responsible, environmentally conscious, and health-oriented citizens (Rieckmann, 2017). Schools, as foundational institutions of learning, provide an ideal platform for introducing sustainability-oriented practices that foster experiential learning and holistic development among students. In recent years, school vegetable gardens have gained increasing attention as an effective educational intervention that integrates academic learning with practical exposure to agriculture, environmental conservation, nutrition, and community engagement. These gardens are increasingly recognized as effective tools for promoting sustainability education and developing life skills among school children.

School vegetable gardens contribute beyond food production by serving as experimental laboratories where students actively

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participate in planting, nurturing, and harvesting crops (Blair, 2009). Through this process, students gain hands-on knowledge of ecological processes, sustainable resource use, and food systems. Such gardens have been reported to enhance environmental awareness, promote healthy dietary behaviours, strengthen social interaction, and encourage leadership and responsibility among students.

In addition to educational and environmental benefits, school vegetable gardens also contribute to economic and social development. Students learn concepts related to cost savings, efficient resource utilization, composting, recycling, and value addition through direct participation in garden management activities. In some schools, surplus produce from gardens is utilized for mid-day meal programmes or sold locally, thereby creating awareness regarding income generation and entrepreneurship. School gardens further strengthen community participation by involving teachers, parents, and local stakeholders in planning and maintenance activities. Such collaborative efforts promote collective responsibility, participatory governance, and stronger school-community relationships. Recent literature also suggests that engagement in gardening activities supports students' physical and mental well-being by reducing stress, encouraging physical activity, and promoting healthy food consumption habits.

As most existing studies focus on isolated outcomes such as nutrition or environmental awareness, with limited attention to the integrated economic, social, governance, and well-being dimensions. Moreover, there is a lack of standardized and validated instruments (Durlak et al., 2011) to systematically measure the multifaceted potential of school vegetable gardens, particularly from the students' perspective. A scientifically developed measurement scale can provide reliable insights into how effectively school vegetable gardens contribute to holistic development and sustainability education (DeVellis & Thorpe, 2021; Gupta et al., 2022; Kademani et al., 2025).

In view of these research gaps, the present study was undertaken to construct and standardize a comprehensive instrument for assessing the multifaceted potential of school vegetable gardens among students. The proposed scale aims to provide a reliable and valid framework encompassing economic, environmental, social, governance, and health & well-being dimensions. Such an instrument would facilitate systematic evaluation of school gardening initiatives and contribute to evidence-based planning, implementation, and policy formulation for strengthening sustainability-oriented educational practices.

METHODOLOGY

A structured and methodical approach was adopted to construct a scale designed to assess the multidimensional potential of school vegetable gardens. The development process was guided by established principles of attitude and perception scale construction (Edwards & Kilpatrick, 1948; Supe & Singh, 1976). In the initial stage, a comprehensive list of statements was generated through an in-depth review of relevant literature along with consultations with specialists in agricultural extension, urban agriculture, and school gardening to ensure inclusion of all important aspects.

Subsequently, the drafted items were subjected to content validation through expert review and focus group discussions to evaluate their clarity, relevance, and redundancy. Based on expert feedback, the statements were refined and screened according to the criteria proposed by Edwards and Kilpatrick (1948), including clarity of expression, singularity of meaning, and avoidance of ambiguous or extreme wording. A relevancy assessment (pilot study) was then conducted in which respondents rated each item on a five-point continuum ranging from "not at all relevant" to "highly relevant." After pilot testing the final refinement was carried out, followed by which reliability (Cronbach alpha and Spearmann coefficient) and validity (Average variance extracted) of each item was computed using RAISINS and SPSS software which led to the development of a theoretically sound and empirically reliable scale for measuring the diverse potential of school vegetable gardens.

RESULTS

Identification of dimension

The identification of dimensions to assess the multifaceted potential of vegetable garden were carried out using comprehensive review of literature and discussion with experts to have necessary modifications to suit the school vegetable garden context. Based on that, five major dimensions were found to be more appropriate for evaluating the multifaceted potential of vegetable garden in schools namely, economic, environment, social, governance and health & well-being dimensions.

Compilation and revision of items

A set of seventy-five items about the diverse potential of school vegetable gardens were gathered from a variety of sources, including recommendations from specialists in urban agriculture and extension education. The fourteen criteria as proponated by Likert (1932), Thurstone (1946); Edwards (1957) were then used to modify these statements. Of this, 66 statements that were unambiguous and clear were kept after modification.

Relevancy of the statements

Initially, 66 statements were created to assess the school vegetable garden's diverse potential. A panel of fifty specialists, including scientists, professors, and extension personnel from Universities in the discipline of agricultural extension, urban agriculture, and school gardening, reviewed these statements. A Likert scale of five point continuum was given to the experts to evaluate each statement's relevance: Highly Relevant (5) and Not Relevant at all (1) whereas Relevant (4), Undecided (3), Not Relevant (2) were scored this way. Each item was carefully reviewed and scored by 36 specialists of the 50 experts that were consulted based on their expertise in the area of this study. Following the principles as established by Edwards (1969); Raj and Thomas (2022); Sownthariya et al. (2026) those that were unspecific, unclear, or deemed to be irrelevant based on the relevance ratings were eliminated. The Relevancy Scores (%) of each item was then estimated by the formula:

$$\text{Relevancy score (\%)} = \frac{\text{Total scores obtained on each items}}{\text{Maximum possible score}} \times 100$$

The Item-Content Validity Index (I-CVI) approach was used to verify the 66 items (Lynn, 1986). As recommended by Polit and Beck (2006), items with a CVI value of 0.85 or above were kept. Following this, 55 statements with a relevancy score of 80% or more were finalised in five categories.

Analysis of item (Index of discrimination)

The t-statistic was determined in order to examine each aspect. Using the method described by Edwards (1957), this helps determine how well each statement distinguishes respondents with high felt potential of vegetable garden from those with low felt potential of vegetable garden. Fifty five statements were examined to determine whether they could possibly be employed to assess the school vegetable garden's diverse potential. 36 responders, including teachers and pupils from non-sample schools, were chosen for this. Each statement was given a five-point rating by the participants, ranging from Strongly Agree to Strongly Disagree. Negative comments were scored in the opposite sequence from positive items, which were scored as 5, 4, 3, 2, and 1. The responders were sorted from top to lowest based on their overall ratings. The low group consisted of the bottom 25% and the high group of the top 25%. The "t" value formulae was used to estimate which statements would effectively variate between groups with high and low perceptions. The following formula was then used to determine the t-value (critical ratio) for each item:

$$t = \frac{XH - XL}{\sqrt{\frac{\left[\frac{\sum XH^2 - (\sum XH)^2}{N}\right] + \left[\frac{\sum XL^2 - (\sum XL)^2}{N}\right]}{N(N-1)}}}$$

Where, XH = the mean score of a given statement from the high group, XL = The mean score of the same statement from the lowest group, ΣXH^2 = Sum of the squares of the individual scores on a given statement for high group, ΣXL^2 = Sum of the squares of the individual scores on a given statement for low group, ΣXH= Summation of the scores on given statement for high group, ΣXL= Summation of the scores on given statement for low group, N= Number of respondents in each group

As a consequence of the assessment, 43 statements with t-critical values greater than 2.306 at the 0.05 level of significance were refined for inclusion in the scale. Five major dimensions were used to finalise and classify these products of multifaceted potential of school vegetable garden: Economic (7 items), Environment (9 items), Social (7 items), Governance (5 items), and Health & well-being (15 items).

Reliability of the scale

To ensure the precision and consistency of the scores, the measurement tool's reliability was evaluated. Internal consistency was calculated using Cronbach's Alpha and the split-half method (Collins, 1996; Ray & Mondal, 2011; Shitu et al., 2018; Meethal & Thomas, 2024). The Spearman Brown formula was utilized to measure the split half reliability coefficient. The scale's great reliability was demonstrated by the results. In particular, a higher degree of internal consistency was shown by Cronbach's Alpha (α) of 0.983. For the 43-item test, Cronbach's alpha was computed by the following formula:

$$\alpha = (N / (N - 1)) \times [\, 1 - (\Sigma \sigma i^2 / \sigma T^2)]$$

Where, N = Number of statements in the scale, σi^2 = Variance of each individual statement (i = 1 to N), $\Sigma \sigma i^2$ = Sum of the variances of all statements, σT^2 = Variance of the total score (sum of all items for each respondent)

The scale's reliability was further confirmed by the split-half reliability coefficients, which were 0.954 when determined using the Spearman-Brown and Guttmann formulas.

Split half reliability,

$$r1/2 = \frac{(N \Sigma XY - (\Sigma X)(\Sigma Y)}{\sqrt{\Sigma[N\Sigma X^2 - (\Sigma X)^2]\,[N\,\Sigma Y^2 - (\Sigma Y)^2]}}$$

Where, X = Scores of odd items, Y= Scores of even items, ΣX =sum of the scores of the odd items, ΣY = sum of the scores of the even items, ΣX^2 = sum of squares of the odd items, ΣY^2 = sum of squares of the even items.

Reliability co-efficient of the scale, (Spearman-brown formula)

$$R = 2\, r1/2 \,/\, 1 + r1/2$$

Where, R = Reliability coefficient of the test, r1/2 = Reliability coefficient of the half test

Table 1. Reliability Statistics (Split half reliability) 1

Cronbach's Alpha	Part 1	Value	.971
		N of Items	22[a]
	Part 2	Value	.966
		N of Items	21[b]
	Total N of Items		43
Correlation Between Forms			.913
Spearman-Brown Coefficient	Equal Length		.954
	Unequal Length		.954
Guttman Split-Half Coefficient			.954

[a]The items are: VAR00001 - VAR00022
[b]The items are: VAR00023- VAR00043.

Table 2. Reliability Statistics (Cronbach alpha) 2

Cronbach's Alpha	N of Items
0.983	43

Validity of the scale

Validity is vital to make sure a research instrument incorporates all the meant statements and enables credible and reliable results (Singh, 2019; Tripathy et al., 2026). Convergent validity was used here to ensure the validity of the instrument created to evaluate the diverse potential of school vegetable gardens. Principal component extraction with varimax rotation was used in an Exploratory Factor Analysis (EFA) to ensure the underlying categories of the construct and further confirm the validity of the scale. The convergent validity was confirmed by the EFA, which showed good loading coefficient across all the dimensions with loadings above 0.60 and an overall Average Variance Extracted (AVE) of 0.840. Based on this assessment, a final tool measuring the multifaceted potential of school vegetable garden was developed, which consisted of 43 statements.

Table 3. Descriptive statistics on multifaceted potential of vegetable garden

S.No.	Statements	t-value	Extraction	R2	AVE
I	Economic dimension				
1	The school garden helps to reduce expenditure on vegetable purchases	4.5355	0.867	0.752	0.849
2	Vegetables grown in the garden can be sold to generate income.	3.1081	0.817	0.667	
3	Budget allotted by the school for the garden is economically justified.	2.345	0.855	0.731	
4	I have started small gardening at home to reduce household vegetable expenses.	2.5298	0.896	0.803	
5	After working in the school garden, I consider gardening as a possible future career	2.4751	0.804	0.646	
6	The school garden does not help in saving or earning money.	4.6031	0.889	0.790	
7	The gardening skills I have learnt can help me earn pocket money.	4.8799	0.815	0.664	
II	Environment dimension				
1	I have learnt how plants grow and what they require	3.2771	0.896	0.803	0.855
2	The garden enhances the aesthetic environment of the school	4.4721	0.824	0.679	
3	I think gardening is a sustainable eco-friendly practice which all the other schools should adopt.	6.0999	0.882	0.778	
4	Gardening promotes efficient water use and recycling practices.	6.825	0.925	0.856	
5	Gardening helps to reduce heat in school premises and cities	4.8799	0.894	0.799	
6	Growing vegetables in school gardens reduces the need for transported food and helps lower greenhouse gas emissions.	5.3758	0.796	0.634	
7	School gardening supports biodiversity conservation by attracting insects, birds, and other beneficial organisms.	3.2771	0.847	0.717	
8	Increased vegetable production in the school makes the school self-reliant.	2.6666	0.75	0.563	
9	Urban school vegetable gardens do not contribute to sustainability	6.9282	0.877	0.769	
III	Social dimension				
1	The garden helped us learn about sharing.	7.2488	0.737	0.543	0.800
2	I made new friends while working in the garden	3.5000	0.734	0.539	
3	Gardening has promoted sense of belonging among us	5.4285	0.853	0.728	
4	Gardening has provided space for sharing our ideas	4.6031	0.755	0.570	
5	Gardening activity has increased my active participation in other school activities	3.2771	0.878	0.771	
6	We solved problems together during garden work.	6.0083	0.787	0.619	
7	I enjoyed when students from different classes worked together.	7.2335	0.853	0.728	
IV	Governance dimension				
1	I feel the decisions about the garden are made in a fair way.	6.0083	0.93	0.865	0.863
2	There are regular meetings or discussions about the garden	4.0971	0.837	0.701	
3	I feel responsible when I'm given a garden task	2.8168	0.78	0.608	
4	We have leaders among ourselves to take initiatives regarding garden	11.9392	0.92	0.846	
5	My teachers trusted me with garden responsibilities	2.4494	0.848	0.719	
V	Health and well being				
	Physical health				
1	Working in school garden increases my daily physical activity	11.3137	0.852	0.726	0.833
2	Gardening helps me stay physically active even in urban environment	5.547	0.779	0.607	
3	Gardening reduces the amount of time I spend sitting or using digital devices.	9.9469	0.929	0.863	
4	Gardening makes me feel tired without any benefits	14.5	0.864	0.746	
	Mental and emotional well-being				
5	Spending time in the school garden helps me feel relaxed	11.3137	0.812	0.659	
6	Gardening improves my mood during school day	11.0864	0.821	0.674	
7	Gardening helps to reduce my stress	8.3152	0.772	0.596	
8	Involvement in school garden improves my concentration in class	6.4874	0.778	0.605	
9	Gardening creates a sense of accomplishment in me	6.7823	0.86	0.740	
	Nutritional awareness and behaviour				
10	I am conscious about eating fresh vegetables after participating in gardening	3.092	0.767	0.588	
11	I understand the importance of safe and healthy food because of the garden	6.825	0.883	0.780	
12	I prefer fresh food items over processed snacks and junk food	4.8799	0.904	0.817	
13	I try to motivate my family to include vegetables in the meal and to grow vegetables at home	5.3758	0.797	0.635	
	Social, emotional integration				
14	Gardening helps me feel connected with other students	3.2771	0.879	0.773	
15	Working together in the garden improves my overall sense of well-being	2.6666	0.803	0.645	
	Overall AVE = 0.849 + 0.855 + 0.800 + 0.863 + 0.833 = 0.840				

Composite Reliability (CR) is calculated as follows:

$$CR = \frac{(\Sigma\lambda i)^2}{(\Sigma\lambda i)^2 + \Sigma(1-\lambda i^2)}$$

Where, λi = Standardized factor loading of item I, $1+ \lambda i$ = Error variance of item, $\lambda^2 i$ = variance explained by the item

$$CR = \frac{(36.046)^2}{(36.046)^2 + 12.658} = 0.990$$

DISCUSSION

The present study resulted in the development of a scientifically validated and structured instrument for assessing the multifaceted potential of school vegetable gardens among students. The final scale consisted of 43 items grouped under five dimensions, namely Economic, Environmental, Social, Governance, and Health & Well-being. The emergence of these five dimensions reflects the inherently multidisciplinary nature of school vegetable gardens and their contribution to sustainability-oriented education. School gardens are not limited to agricultural learning alone; rather, they influence students' economic understanding, environmental responsibility, social interaction, participatory practices, and personal well-being simultaneously. The dimensional structure identified through factor analysis therefore confirms that school vegetable gardens function as holistic educational platforms capable of supporting multiple developmental outcomes.

Among the five dimensions, Health & Well-being emerged with the largest number of items (15 items). This is because of the broader and more visible direct influence of gardening activities on students' physical, mental, emotional, and behavioural development. Students involved in school gardening activities are exposed to healthy dietary practices, physical activity, stress reduction, emotional satisfaction, and improved social and psychological well-being. In addition, health and well-being aspects are often more observable and personally experienced by students compared to economic or governance dimensions, resulting in greater variability and representation during scale development. Previous studies have also highlighted that school gardens significantly influence students' nutritional awareness, food preferences, emotional balance, and overall quality of life, which may explain the higher concentration of valid items under this dimension.

The exploratory Factor Analysis (EFA) demonstrated better item loadings across the five dimensions, with all factor loadings exceeding the threshold of 0.60. Each sub-categories reported above the suggested benchmark for validity (Hair et al., 2020), indicating that the constructs adequately accounted for a substantial proportion of variance. The observed values were 0.849 for Economic, 0.855 for Environment, 0.800 for Social, 0.863 for Governance, and 0.833 for Health and Well-being. The overall Average Variance Extracted (AVE) was 0.840, further ensuring the convergent validity of the instrument (Fornell & Larcker, 1981). The final 43-item scale exhibited great internal consistency, as proven by a Cronbach's alpha of 0.983. In addition, split-half reliability analysis yielded strong results, with both the Spearman–Brown and Guttman split-half coefficients recording values of 0.954.

The final validation process lead to a robust forty- three item tool measuring multifaceted potential of vegetable gardens in schools under five dimensions: Economic (7 items), Environment (9 items), Social (7 items), Governance (5 items), and Health & well-being (15 items). The collective item's scientific and conceptual consistency was further ensured by extensive verification.

The developed scale has significant implications for extension education and sustainability-oriented programmes. Extension professionals, educators, and development agencies can utilize the instrument to assess students' perceptions regarding school vegetable gardens and evaluate programme effectiveness across schools and communities. The scale can serve as a diagnostic tool for identifying strengths and gaps in school gardening initiatives and for designing targeted interventions related to nutrition education, environmental awareness, student participation, and community engagement. Furthermore, the instrument may support evidence-based decision-making, resource allocation, policy formulation, and capacity-building efforts undertaken by government departments, schools, and non-governmental organizations involved in school sustainability programmes.

Despite its strengths, the study has certain limitations. The scale was developed and validated within a specific educational and socio-cultural context, which may limit its direct generalization to other regions or educational systems without further testing. In addition, the instrument primarily captures students' perceptions and does not include the perspectives of teachers, parents, or administrators.

CONCLUSION

The study developed and validated a comprehensive 43-item scale to assess the multifaceted potential of school vegetable gardens across five key dimensions: Economic, Environmental, Social, Governance, and Health & Well-being. These dimensions reflect the holistic contributions of school gardens to students' learning, behaviour, and overall development. The systematic scale construction process ensured strong content validity, high internal consistency, and satisfactory convergent validity, confirming the robustness and reliability of the instrument. The high Cronbach's alpha value and favourable Average Variance Extracted scores indicate that the scale effectively captures students' perceptions across multiple dimensions. The standardized scale serves as a psychometrically sound and holistic tool for systematic assessment and comparison across schools, helping to identify strengths and gaps in existing garden initiatives. It provides valuable insights for researchers, educators, and policymakers, thereby supporting evidence-based planning, decision-making, and effective implementation of school vegetable garden programs while contributing to sustainability-oriented educational research.

DECLARATIONS

Ethics approval and informed consent: Informed consent from the specialist possessing specialized knowledge in urban agriculture, extension education were sought to obtain validation. From their feedback, a pilot study was carried out with randomly selected students from non -sampling schools.

Conflict of interest: The authors declare that this research was carried out without any financial contribution that could be considered as potential conflicts of interest among. The authors further affirm that they independently reviewed, revised, and edited the manuscript throughout its preparation and accept the final content of this publication.

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Research Tool

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Construction and Validation of Knowledge Test on Indigenous Technical Knowledge Practices

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HIGHLIGHTS

- A standardized knowledge test was designed to evaluate tribal farmers' understanding of Indigenous Technical Knowledge practices across agriculture, indigenous crops, tools, food processing, pest management, livestock healthcare, and folk traditions.
- Content validation by 60 experts retained 43 items from an initial pool of 66 items using Relevancy Weightage (RW), Mean Relevancy Score (MRS) and Overall Mean Relevancy Score (OMRS).
- Item analysis using difficulty index, discrimination index, and point-biserial correlation finalized 35 valid items. The developed test showed excellent internal consistency with Cronbach's alpha value of 0.93.

ARTICLE INFO

Keywords: Indigenous technical knowledge, Knowledge test, Tribal farmers, Item analysis, Reliability, Validity.

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ABSTRACT

Indigenous Technical Knowledge (ITK) is vital to tribal farming systems, supporting local resource use, biodiversity conservation, food security, ethnoveterinary care, indigenous food processing and climate adaptation. However, the absence of standardized instruments restricts assessment of ITK knowledge gaps and planning of need-based extension interventions. This study constructed and validated a knowledge test to assess tribal farmers' knowledge of ITK practices. The target population comprised tribal farmers possessing or practising ITK in agriculture and allied activities in the study area. Initially, 66 items were developed through literature review, expert consultation and field-level understanding of ITK domains. The item pool was content-validated by 60 experts. Relevancy Weightage (RW), Mean Relevancy Score (MRS) and Overall Mean Relevancy Score (OMRS) were computed using established procedures. Based on relevancy screening, 43 items were retained and administered to 60 non-sample farmers for pilot testing. Difficulty index, discrimination index and point-biserial correlation were calculated. Item statistics showed difficulty values (0.433–0.667) and discrimination values (0.333–0.567), confirming moderate difficulty and discrimination. Finally, 35 items were retained. Cronbach's alpha was 0.93, indicating excellent internal consistency. The test was valid, reliable and suitable for assessing ITK knowledge, diagnosing gaps, evaluating capacity-building programmes and supporting documentation, preservation and promotion of ITK.

INTRODUCTION

Indigenous Technical Knowledge (ITK) represents a cumulative body of locally evolved wisdom, skills and practices developed by farming communities through long-term interaction with their agro-ecological, social and cultural environments. In tribal societies, such knowledge is not merely a set of techniques; it is embedded in livelihood systems, resource-use behaviour, healthcare traditions, ritual practices, weather interpretation, communication networks and intergenerational learning. Studies on tribal communities have

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shown that indigenous knowledge continues to guide decision-making in agriculture, livestock management, natural resource conservation and household-level problem solving, particularly in areas where formal scientific advisory systems are either limited or less accessible (Lenka & Satpathy, 2020; Gavit et al., 2013).

The relevance of ITK has become more prominent in the context of sustainable agriculture, climate variability and conservation of biocultural heritage. Traditional weather prediction among tribal communities of Mizoram, for example, is based on bioindicators such as behaviour of insects, birds, animals, plants, clouds and winds, demonstrating the observational depth of local ecological knowledge (Chinlampianga, 2011). Similarly, indigenous knowledge has been reported to contribute to drought risk reduction and resilience among communal farmers, especially where resource-poor farming households depend on locally available coping strategies (Muyambo et al., 2017). In the Indian tribal context, ITK is closely linked with medicinal plants, sacred groves, rituals, food systems and community health practices (Roy et al., 2023; Roy et al., 2025). Ethnomedicinal studies among the Karbi tribe of Assam documented the use of sacred-grove plant species for treating different ailments, while recent work in Assam recorded rich traditional knowledge associated with medicinal plants and emphasized its documentation for future pharmacological and conservation research (Baidya et al., 2020; Kalita et al., 2024). Among the tribes of Malkangiri district, Odisha, plants and plant parts are used for rituals as well as medicinal purposes, reflecting the inseparable relationship between ecological resources and cultural belief systems (Bala et al., 2020).

Recent studies on the Bonda tribe further indicate that indigenous medicinal knowledge is transmitted through elders, Desaris and community-based networks and that preservation of such knowledge is essential for sustaining tribal identity, cultural continuity and health security (Kumari et al., 2024; Sahoo et al., 2024). However, the continuity of ITK is increasingly threatened by modernization, declining oral transmission, secrecy of knowledge holders, weakening apprenticeship systems and inadequate documentation. Traditional knowledge often remains tacit, orally transmitted and vulnerable to loss when knowledge holders pass away. At the same time, intellectual property concerns and risks of misappropriation demand ethically sensitive documentation and validation mechanisms. Indigenous cultural practices such as storytelling, music, dance and ritual communication also function as knowledge-transfer mechanisms, indicating that ITK must be understood within its cultural context rather than only as isolated technical information (Borunda & Murray, 2019; Nayak et al., 2011). Despite the growing documentation of indigenous practices, limited empirical attention has been paid to developing standardized tools for measuring farmers' knowledge of ITK practices. A valid and reliable knowledge test is therefore necessary to quantify the extent of knowledge, identify knowledge gaps, compare knowledge levels across respondent categories and support need-based extension interventions. Construction and validation of such a test will provide a scientific basis for assessing tribal farmers' knowledge while respecting the cultural, ecological and practical significance of Indigenous Technical Knowledge.

METHODLOGY

The study adopted an instrument-development research design to construct and validate a standardized knowledge test for measuring tribal farmers' knowledge of Indigenous Technical Knowledge (ITK) practices. The procedure involved item generation, expert validation, relevancy assessment, item analysis, validity testing and reliability estimation. The target population comprised tribal farmers possessing or practising ITK in agriculture and allied sectors in the study area. For content validation, 60 subject-matter specialists from Agricultural Extension, Agronomy, Entomology, Plant Pathology, Animal Science, Forestry, Tribal Studies and allied disciplines constituted the expert panel. For pilot testing and item analysis, 60 non-sample tribal farmers, comparable to the main population but excluded from the final sample, were selected. Thus, 120 response sheets were used: 60 expert sheets (50.00%) and 60 pilot schedules (50.00%) for content validation, field testing, item analysis and reliability estimation. Since classical test theory was followed and no predictive modelling was involved, no training–testing split was required; complete pilot data were used for validation. Initially, 66 items were prepared through review of research articles, extension publications, ethnobotanical studies, ITK documentation reports and secondary sources covering agriculture, indigenous crops, food processing, pest management, ethnoveterinary healthcare, natural resource management and folk traditions. Expert consultations ensured conceptual relevance, technical accuracy, cultural appropriateness and field suitability. Items were framed in multiple-choice and Yes/No formats and rated by 60 experts on a three-point continuum: Most Relevant (3), Relevant (2) and Not Relevant (1). Relevancy Weightage (RW), Mean Relevancy Score (MRS) and Overall Mean Relevancy Score (OMRS) were computed following established procedures (Vijayan et al., 2022; Vijayan et al., 2023; Singh et al., 2026). The formulae used were as follows:

$$RW = \frac{(MR \times 3) + (R \times 2) + (NR \times 1)}{MPS}$$

$$MRS = \frac{(MR \times 3) + (R \times 2) + (NR \times 1)}{N}$$

where MR, R and NR indicate experts' ratings; MPS is maximum possible score; and N is the number of experts. Items with RW $\geq$ 0.80 and acceptable MRS were retained; marginally lower but essential ITK items were revised as per expert suggestions. After screening, 43 items were administered to 60 non-sample tribal farmers. Correct answers were scored one and incorrect answers zero. Total scores were arranged in descending order and divided into six equal groups (G1–G6). For item analysis, only G1, G2, G5 and G6 were used, excluding the middle groups, following classical test theory and educational measurement principles (Ebel & Frisbie, 1991). The Difficulty Index (P) was calculated as:

$$P = \frac{\text{Number of respondents answering correctly}}{\text{Total number of respondents}} \times 100$$

Items with difficulty values between 30 and 70 per cent were retained. The Discrimination Index (E 1/3) was computed as:

$$E_{1/3} = \frac{(S_1 + S_2) - (S_5 + S_6)}{N/3}$$

Where, S_1, S_2, S_5 and S_6 represent the number of correct responses in respective groups. Items with discrimination values between 0.30 and 0.80 were selected. Internal validity was examined using the point-biserial correlation coefficient:

$$r_{pbis} = \frac{M_p - M_q}{SD}\sqrt{PQ}$$

where Mp = mean total score of respondents answering the item correctly; Mq = mean total score of respondents answering the item incorrectly; SD = standard deviation of total scores; P = proportion of correct responses; and Q = 1 - P. Items with positive and acceptable item-total association were prioritized, and items with poor discrimination, extreme difficulty or weak content relevance were deleted or revised. The internal consistency of the finalized knowledge test was assessed using Cronbach's alpha, a standard reliability coefficient for multi-item tests. The obtained alpha value was interpreted to determine whether the selected items measured the intended knowledge construct consistently.

RESULTS

Expert relevancy assessment

Out of 66 initially developed items, 43 items satisfied the prescribed relevancy criteria and were retained for item analysis. The retained items covered major domains of ITK, including general indigenous agricultural knowledge, indigenous crop varieties and food plants, traditional agricultural tools, food processing and preservation, cultivation practices, pest and disease management, livestock and poultry healthcare, agricultural festivals and folk traditions. The expert-screening process confirmed that the retained items were conceptually meaningful, technically sound and contextually relevant for assessing tribal farmers' knowledge of ITK practices.

Item analysis and final item selection

The 43 selected items were administered to 60 non-sample tribal farmers for item analysis. After applying difficulty, discrimination and item-total association criteria, 35 items were retained in the final knowledge test. The difficulty index values of the final items ranged from 0.433 to 0.667, showing that the items were of moderate difficulty and suitable for field-level knowledge assessment. The discrimination index values ranged from 0.333 to 0.567, indicating that the items could differentiate between respondents with higher and lower knowledge levels. The point-biserial correlation values were positive, and most of the retained items showed acceptable item-total association, confirming their contribution to the overall knowledge construct. Items with poor psychometric performance were either deleted or revised before finalization.

Validity analysis

Content validity was established through systematic item generation and expert judgment. The involvement of specialists from multiple disciplines ensured that the knowledge test represented the major conceptual and practical domains of ITK. Construct validity was strengthened through item analysis and point-biserial correlation. Since the retained items were positively associated with the total score and demonstrated acceptable discrimination, the final test was able to distinguish respondents with relatively higher and lower levels of ITK knowledge.

Reliability analysis

The final 35-item knowledge test showed a Cronbach's alpha value of 0.93. This value indicates excellent internal consistency and confirms that the items functioned cohesively to measure a single broad construct, namely knowledge of Indigenous Technical Knowledge practices. The reliability result supports the use of the test for empirical research, field diagnosis, training evaluation and extension planning.

DISCUSSION

The present study was undertaken to develop and validate a standardized knowledge test for measuring regarding Indigenous Technical Knowledge Practices. The findings demonstrate that the systematic procedure followed in the study, comprising item generation, expert validation, relevancy assessment, item analysis, validity testing, and reliability estimation, was effective in producing a scientifically robust and psychometrically sound instrument.

The reliability coefficient obtained in the present study was 0.93, indicating excellent internal consistency of the final knowledge test. This result is in agreement with the findings of Priyadarshini et al. (2021), who reported a comparable reliability coefficient of 0.904 in a similarly structured knowledge test. The high reliability value confirms that the items included in the final instrument were internally coherent and measured the intended construct with consistency. This finding also supports the methodological assumption that knowledge tests developed through systematic item selection, expert screening, and psychometric refinement are more likely to achieve high reliability.

The content validity of the instrument was strengthened through the involvement of experts from relevant disciplines. Their evaluation ensured that the test covered all important dimensions of Indigenous Technical Knowledge, including General Indigenous Agricultural Knowledge, Indigenous Crop Varieties and Food Plants, Traditional Agricultural Tools, Food Processing and Preservation, Cultivation Practices, Pest and Disease Management, Livestock and Poultry Healthcare, and Agricultural Festivals and Folk Traditions. Such multidisciplinary expert involvement enhanced the technical correctness, contextual relevance, and field applicability of the test.

The discrimination index values obtained in the study indicate that the selected items were capable of differentiating between respondents with high and low levels of knowledge. This finding is consistent with the observations of Kumar et al. (2016), Vijayan et al. (2022), and Vijayan et al. (2023), Singh et al., 2026, who emphasized the importance of discrimination power in the development of valid knowledge tests. Items with acceptable discrimination values improve the diagnostic capacity of a test by identifying meaningful differences in respondents' knowledge levels.

The point-biserial correlation values further confirmed the construct validity of the test. Since most retained items recorded rpbis values greater than 0.25, it may be inferred that these items were strongly associated with the total knowledge score and

Table 1. Relevancy, difficulty, discrimination and point-biserial correlation scores used for item selection and item analysis

S.No.	Items	RW	MRS	P	E 1/3	rpbis
1.	Indigenous Technical Knowledge mainly refers to: A. Imported farm technology B. Locally evolved knowledge and practices C. Only laboratory-based knowledge D. Only government schemes	0.96	2.88	0.600	0.400	0.239
2.	Does Indigenous Technical Knowledge contribute to sustainable agriculture? Yes / No	0.91	2.72	0.600	0.400	0.550
3.	Indigenous farming reduces dependence on external inputs mainly through the use of: A. Local resources B. Imported pesticides C. Hybrid seeds only D. Heavy machinery only	0.82	2.45	0.500	0.500	0.395
4.	Is traditional ecological knowledge relevant for farming systems? Yes / No	0.84	2.53	0.633	0.367	0.406
5.	Indigenous agricultural practices support biodiversity conservation by promoting: A. Crop diversity B. Monocropping only C. Excessive chemical use D. Complete removal of local crops	0.81	2.43	0.600	0.400	0.345
6.	Can indigenous practices help farmers cope with climate variability? Yes / No	0.85	2.55	0.600	0.400	0.581
7.	Knowledge of indigenous potato varieties is important because they are often: A. Locally adapted B. Always imported C. Unrelated to food security D. Used only for decoration	0.81	2.43	0.633	0.367	0.290
8.	Should awareness of traditional taro varieties be included in an ITK knowledge test? Yes / No	0.82	2.47	0.567	0.433	0.475
9.	Identification of traditional vegetable crops helps assess farmers' knowledge of: A. Local food plants B. Tractor repair C. Market taxation D. Chemical industries	0.84	2.52	0.633	0.367	0.514
10.	Indigenous vegetables and fruits are important mainly for: A. Dietary diversity and nutrition B. Increasing pesticide residue C. Eliminating local food habits D. Replacing all cereals	0.90	2.70	0.567	0.433	0.528
11.	Is knowledge of local crop varieties cultivated by tribal farmers relevant? Yes / No	0.81	2.43	0.500	0.500	0.387
12.	Traditional agricultural tools are important indicators of: A. Indigenous farming knowledge B. Urban lifestyle C. Factory production D. Banking literacy	0.81	2.43	0.567	0.433	0.611
13.	Does identification of traditional farm implements reflect tribal agricultural knowledge? Yes / No	0.85	2.55	0.567	0.433	0.551
14.	Indigenous farming tools are usually developed according to: A. Local soil, crop and labour conditions B. Foreign designs only C. Urban construction needs D. Industrial standards only	0.81	2.43	0.600	0.400	0.421
15.	Traditional rice beer preparation is an example of: A. Indigenous food processing B. Chemical pest control C. Mechanized irrigation D. Seed certification	0.81	2.43	0.633	0.367	0.256
16.	Should traditional methods of preparing Khari be included in the knowledge test? Yes / No	0.91	2.72	0.667	0.333	0.265
17.	Nakham is traditionally associated with preservation of: A. Fish B. Paddy seed C. Milk D. Fertilizer	0.84	2.52	0.533	0.467	0.464
18.	Are indigenous packaging materials used in food storage and transport? Yes / No	0.84	2.52	0.567	0.433	0.460
19.	Mulching in traditional cultivation is mainly useful for: A. Conserving soil moisture B. Increasing soil erosion C. Burning crop plants D. Reducing organic matter	0.87	2.62	0.567	0.433	0.370
20.	Does mixed cropping help in reducing production risk? Yes / No	0.82	2.47	0.600	0.400	0.543
21.	Traditional fertilizer practices commonly involve the use of: A. Farmyard manure and compost B. Plastic waste C. Industrial acids D. Synthetic dyes	0.82	2.47	0.600	0.400	0.257
22.	Smoke-based pest control is traditionally used to: A. Repel insects and pests B. Increase pest multiplication C. Improve seed colour D. Replace irrigation	0.83	2.50	0.533	0.467	0.165
23.	Is ash application used in some indigenous pest-management practices? Yes / No	0.90	2.70	0.533	0.467	0.382

Table 1. Relevancy, difficulty, discrimination and point-biserial correlation scores used for item selection and item analysis

S.No.	Items	RW	MRS	P	E 1/3	rpbis
24.	Biological pest management mainly involves the use of: A. Natural enemies or biological agents B. Only synthetic pesticides C. Plastic sheets D. Chemical dyes	0.87	2.62	0.567	0.433	0.671
25.	Can birds help in controlling harmful insects in paddy fields? Yes / No	0.88	2.65	0.567	0.433	0.242
26.	Indigenous disease-control practices are generally based on: A. Local materials and traditional experience B. Imported machinery only C. Computer models only D. Chemical fertilizer only	0.92	2.75	0.433	0.567	0.314
27.	Indigenous remedies for cattle diseases are mostly based on: A. Medicinal plants and local healing practices B. Imported feed only C. Artificial insemination only D. Mechanized ploughing	0.89	2.68	0.600	0.400	0.550
28.	Should traditional remedies for goat diseases be assessed in an ITK knowledge test? Yes / No	0.86	2.57	0.500	0.500	0.395
29.	Ethnoveterinary practices for pig disease management generally include: A. Local medicinal plants and traditional treatment B. Chemical fertilizers C. Harvesting methods D. Soil mapping	0.87	2.60	0.633	0.367	0.406
30.	Should poultry disease prevention methods be included in the ITK knowledge test? Yes / No	0.85	2.55	0.600	0.400	0.345
31.	Medicinal plants are used in traditional animal healthcare mainly for: A. Treating or preventing livestock ailments B. Preparing synthetic fertilizer C. Increasing pesticide residue D. Replacing drinking water	0.91	2.73	0.600	0.400	0.581
32.	Do cultural practices linked with farming reflect indigenous agricultural knowledge? Yes / No	0.84	2.52	0.633	0.367	0.290
33.	Rituals related to crop protection are generally associated with: A. Traditional belief and crop safeguarding B. Soil pollution C. Tractor maintenance D. Seed certification	0.92	2.75	0.567	0.433	0.475
34.	Are seasonal agricultural festivals relevant indicators of indigenous agricultural knowledge? Yes / No	0.87	2.60	0.633	0.367	0.514
35.	Can traditional dances preserve agricultural heritage knowledge? Yes / No	0.82	2.47	0.500	0.500	0.387

contributed substantially to the measurement of knowledge regarding Indigenous Technical Knowledge Practices. Items with low or negative associations were removed, thereby improving the precision and internal validity of the final instrument.

The reduction of the item pool from 66 initially generated items to 35 final items highlights the importance of rigorous item filtration in knowledge-test construction. Such refinement eliminates redundancy, ambiguity, weak discrimination, and irrelevant content while retaining only those items that satisfy both conceptual and statistical standards. A shorter but well-validated test is also more practical for field administration, particularly among farming communities, where lengthy instruments may cause respondent fatigue and reduce data quality.

Overall, the study successfully developed a standardized, valid, and reliable knowledge test for assessing the knowledge regarding Indigenous Technical Knowledge Practices. The final instrument can be used by researchers, extension personnel, training institutions, development agencies, and policymakers to diagnose knowledge gaps, evaluate training effectiveness, design need-based extension programmes, and strengthen knowledge regarding Indigenous Technical Knowledge Practices literacy.

CONCLUSION

The study successfully constructed and validated a standardized knowledge test for measuring tribal farmers' knowledge of Indigenous Technical Knowledge practices. The instrument was developed through a systematic process involving item generation, expert validation, relevancy assessment, item analysis, validity testing and reliability estimation. From an initial pool of 66 items, 43 items were retained after expert screening and 35 items were finalized after item analysis. The retained items showed acceptable difficulty and discrimination values, and the final test recorded excellent internal consistency with a Cronbach's alpha value of 0.93. The developed test is therefore suitable for assessing ITK knowledge among tribal farmers and can be used for identifying knowledge gaps, evaluating training effectiveness and designing need-based extension interventions.

DECLARATIONS

Ethics approval and informed consent: The study was conducted following appropriate ethical considerations. Prior informed consent was obtained from all respondents and their respective organisations before data collection. The respondents were clearly informed about the purpose of the study, and their participation was entirely voluntary. Confidentiality of the information provided by the respondents was duly maintained.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial, financial, or personal relationships that could be construed as a potential conflict of

interest. The authors have thoroughly reviewed, revised, and edited the manuscript and take full responsibility for the final content of this publication.

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Authors' contribution: Shenjuti Chowdhary contributed to conceptualization, data collection, literature review, and preparation of the initial draft of the manuscript. Arun Kumar Singh provided overall guidance, supervision, critical inputs, and intellectual support throughout the study. Priyanka Roy contributed to data organisation, analysis, interpretation of findings, and manuscript refinement. Prashish Singh contributed to methodology development, data interpretation, manuscript editing, final revision, and correspondence. All authors reviewed and approved the final version of the manuscript.

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Development and Validation of Agricultural Human-Wildlife Conflict Tolerance Scale for Farming Households

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HIGHLIGHTS

- A wildlife tolerance scale was developed and validated for buffer zone farmers consisting of 18 items, divided into 4 dimensions using EFA, explaining total variance of 67.41% and a Cronbach's α of 0.836.
- The majority (59.00%) of farmers residing in the buffer zones of Ranipur Tiger Reserve showed a medium level of tolerance.

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ABSTRACT

Agriculture–Human–Wildlife Conflict (AHWC) poses a significant threat to the livelihoods of agricultural households in buffer zones of protected areas across India. Measuring farmers' tolerance toward conflict is essential for designing effective conservation extension practices. The data was collected during March–April 2026 from 200 households residing in the buffer zone of Ranipur Tiger Reserve (RTR), Uttar Pradesh, to develop and validate the Wildlife Tolerance Scale for Buffer Zone Farmers. An initial pool of 50 items was generated and subjected to expert review by nine specialists using Content Validity Ratio (CVR). Items having CVR less than the threshold were removed, resulting in 43 items being tested on the final 200 households. After item-level reliability screening (corrected item–total correlation ≥0.30 and Cronbach's alpha >0.7), 18 items were retained for the main study. Retained items were analysed through Exploratory Factor Analysis (Direct Oblimin rotation). This resulted in four factors i.e. Adaptive Coexistence Behaviour, Coexistence Acceptance, Conservation-Oriented Tolerance, and Damage and Adaptation Tolerance. Final 18 items have a high internal consistency (α = .836) and explain a total variance of 67.41%. The WTS-BZF will provide extension workers and conservation practitioners with a validated instrument for assessing and enhancing wildlife tolerance among farming communities.

INTRODUCTION

Agriculture-Human–Wildlife Conflict (AHWC) is one of the most complex challenges in improving the agricultural livelihoods and biodiversity conservation in the buffer zones of protected areas. In India, the expansion of protected areas and recovery of megafauna populations under Project Tiger results in intense interactions between wildlife and farming communities living in buffer zones (Jhala et al., 2021). Households living in buffer zones routinely experience crop destruction, livestock predation and property damage by wild animals, resulting in significant economic losses and negative attitudes toward conservation efforts (Subedi et al., 2020). Ranipur Tiger Reserve (RTR), located in the

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Chitrakoot district of Uttar Pradesh, India, is a good example of such conflicts occurring in buffer-zone landscapes. Agricultural households in the buffer zones frequently encounter wildlife inhabiting in the RTR, making tolerance an important determinant for long-term coexistence. In this context, tolerance referred to the willingness of farming households to accept the presence of wildlife and bear associated costs without resorting to retaliatory or exclusionary actions (Slagle et al., 2013). Despite the various efforts and policies for conservation tolerance towards wildlife, it is inadequately measured in the context of South Asia. The majority of the tolerance measures were developed for Western or African contexts and do not capture the socio-ecological character of small and marginal farming communities in India (Kansky et al., 2016). Moreover, there is also a gap to measure tolerance towards AHWC among buffer-zone households in Indian reserve landscapes.

Agricultural extension contributes significantly to mediating human–wildlife coexistence by facilitating behavioural change, disseminating conflict-mitigation technologies, and building community capacity (Barua et al., 2013). Extension professionals also assess the baseline of tolerance level in rural households and monitor changes occurs due to the interventions introduced. For the above, they require a psychometrically robust, context-specific measurement tool. Though wildlife tolerance is recognised as an important determinant of successful human–wildlife coexistence, a standardised and contextually appropriate scale for assessing the tolerance level of households residing in the buffer zones of India is lacking. Therefore, the study tries to develop and validate the Wildlife Tolerance Scale for Buffer Zone Farmers (WTS-BZF). It is a measurement tool designed to assess the tolerance level of agricultural households residing in buffer zones toward wildlife in protected-areas. The instrument is expected to support the research, extension planning, and conservation initiatives aimed at fostering sustainable human–wildlife coexistence.

METHODOLOGY

The buffer area of the reserve forest is divided into seven ranges, namely Manikpur I, Manikpur II, Markundi I, and Markundi II, Karvi, Raipura and Bargarh. Four ranges were selected purposively on the basis of closest proximity to the RTR, followed by random village selection. Four villages were selected from each of Manikpur I and Markundi I, and six villages were selected from each of Manikpur II and Markundi II, yielding a total of 20 villages. The variation in village selection is due to differences in area where Manikpur I and Markundi I (2547.98 ha and 3291.34 ha) cover a small area compared to Manikpur II and Markundi II (6647.75 ha and 6331.65 ha). From each village, 10 households were randomly selected, resulting in a final sample of 200 households in the buffer zone. A cross-sectional household survey design was adopted, and data were collected through personal interview using the developed scale. The WTS-BZF was developed following a systematic multi-stage psychometric protocol.

Stage 1 Item Generation, an initial pool of 50 statements was collected through literature review, expert consultation and qualitative field observations (Maurya et al., 2024).

Stage II Content validation, the 50-item pool statements were submitted to a panel of 9 experts, including Subject matter specialists, extension scientists and Forest officers. Each expert rate each item as 'Essential', 'Useful but not essential', or 'Not necessary'. Content Validity Ratio (CVR) was computed for each item using Lawshe's (1975) formula:

$$CVR = (n_e - N/2) / (N/2)$$

For nine experts, the minimum acceptable CVR is 0.78 (Lawshe, 1975). Items with CVR < 0.56 were removed; items with CVR of 0.56 were revised and re-evaluated. This resulted in retention of 43 items.

Stage 3 Testing, the 43-items were used to collect survey data from 200 households living in the buffer-zone of RTR. Items were screened for corrected item–total correlation below 0.30, and improvement of Cronbach's alpha upon item deletion. Following this screening, 18 items were retained for the main study.

Stage 4 Main Study and Construct Validation, the data of the retained 18 scale items were used to check reliability using Cronbach's alpha. Construct validity was checked with Exploratory Factor Analysis (EFA) using Principal Axis Factoring (PAF) using Direct Oblimin rotation. A factorability confirmatory test was performed using Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. Factors were retained based on eigenvalue > 1, communalities $\geq$ 0.40, and pattern matrix loadings $\geq$ 0.50.

RESULTS

Content validity and item reduction

Expert panel reviewed the pool of 50 item and CVR values were used for systematic item reduction. Items TOL20, TOL29, TOL35–TOL37, TOL40 and TOL44 were removed as the CVR values were below the acceptable threshold of 0.56, or due to the overall consensus of the expert ratings that these items lacked sufficient discriminant content for the target population. Items with CVR of 0.56 (TOL10, TOL18, TOL28, TOL38, TOL41–TOL43, TOL46, TOL48) were revised for clarity before including in the final instrument. The CVR results for all 50 items are presented in Table 1. A total of 43 items were retained for final testing after content validation from the experts.

Testing and item screening

The 43-items retained after CVR screening were used for data collection from 200 households residing in the buffer-zone of RTR, Uttar Pradesh. Initially the reliability analysis was done using Cronbach's alpha of 0.688 with 43 items. Items were systematically screened using corrected item–total correlation (CITC) with the criterion that alpha should not improve substantially upon item deletion. Items with CITC < 0.30 were removed (TOL4-TOL12, TOL14-TOL34-TOL50), along with items where alpha-if-deleted exceeded the overall scale alpha. Following these criteria for screening, 18 items were retained. Re-analysis of the retained 18-items result in a substantially improved Cronbach's alpha of 0.836, confirming an adequate internal consistency of the scale. The pilot reliability statistics are presented in Table 2.

Factor extraction

Before analysing EFA, the correlation matrix was assessed (Table 3) to determine the factorability of the 18 items. The Kaiser–

Table 1. Content Validity Ratio (CVR) and testing reliability

Item	Content Validity Ratio (CVR) results for initial 50 items (Expert panel, N = 9)					Testing reliability statistics of before and after item screening (n=200)				
	Essential (ne)	Useful	Not Necessary	CVR	Decision	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item–Total Correlation	Cronbach's α if Item Deleted	Decision
						Before item screening: α = .688, 43 items				
TOL1	9	0	0	1.00	Keep	97.99	92.41	0.345	0.674	Retained
TOL2	8	1	0	0.78	Keep	97.97	93.19	0.304	0.676	Retained
TOL3	9	0	0	1.00	Keep	97.99	93.23	0.310	0.676	Retained
TOL4	9	0	0	1.00	Keep	98.92	95.11	0.272	0.689	Removed
TOL5	8	1	0	0.78	Keep	98.04	98.40	-0.024	0.695	Removed
TOL6	9	0	0	1.00	Keep	98.82	95.64	0.214	0.69	Removed
TOL7	9	0	0	1.00	Keep	98.91	95.18	0.182	0.692	Removed
TOL8	8	1	0	0.78	Keep	98.75	96.03	0.097	0.695	Removed
TOL9	9	0	0	1.00	Keep	98.68	96.74	0.045	0.698	Removed
TOL10	7	2	0	0.56	Revise	98.59	97.15	-0.018	0.702	Removed
TOL11	8	1	0	0.78	Keep	97.40	97.88	-0.020	0.699	Removed
TOL12	9	0	0	1.00	Keep	98.48	96.96	0.019	0.696	Removed
TOL13	8	1	0	0.78	Keep	97.91	93.80	0.342	0.679	Retained
TOL14	9	0	0	1.00	Keep	98.97	94.92	0.258	0.689	Removed
TOL15	8	1	0	0.78	Keep	98.94	95.27	0.241	0.691	Removed
TOL16	9	0	0	1.00	Keep	99.02	98.13	0.245	0.692	Removed
TOL17	9	0	0	1.00	Keep	98.88	95.88	0.126	0.694	Removed
TOL18	7	2	0	0.56	Revise	98.79	96.26	0.081	0.696	Removed
TOL19	9	0	0	1.00	Keep	98.92	91.13	0.435	0.669	Retained
TOL20	6	2	1	0.33	Remove	-	-	-	-	-
TOL21	9	0	0	1.00	Keep	99.15	93.39	0.340	0.676	Retained
TOL22	9	0	0	1.00	Keep	99.07	93.41	0.346	0.675	Retained
TOL23	8	1	0	0.78	Keep	99.30	93.56	0.350	0.676	Retained
TOL24	9	0	0	1.00	Keep	99.29	93.33	0.373	0.675	Retained
TOL25	9	0	0	1.00	Keep	99.24	92.46	0.429	0.672	Retained
TOL26	8	1	0	0.78	Keep	99.19	92.16	0.464	0.670	Retained
TOL27	9	0	0	1.00	Keep	99.29	92.46	0.432	0.672	Retained
TOL28	7	2	0	0.56	Revise	99.28	93.70	0.360	0.676	Retained
TOL29	6	2	1	0.33	Remove	99.21	93.61	0.302	0.676	Retained
TOL30	8	1	0	0.78	Keep	99.00	93.56	0.330	0.676	Retained
TOL31	9	0	0	1.00	Keep	98.99	93.68	0.324	0.677	Retained
TOL32	9	0	0	1.00	Keep	99.06	93.56	0.328	0.676	Retained
TOL33	9	0	0	1.00	Keep	99.03	94.42	0.312	0.680	Retained
TOL34	8	1	0	0.78	Keep	98.71	96.42	0.143	0.694	Removed
TOL35	6	2	1	0.33	Remove	-	-	-	-	-
TOL36	6	2	1	0.33	Remove	-	-	-	-	-
TOL37	6	2	1	0.33	Remove	-	-	-	-	-
TOL38	7	2	0	0.56	Revise	98	96.88	-0.010	0.704	Removed
TOL39	8	1	0	0.78	Keep	98.31	98.34	-0.061	0.707	Removed
TOL40	6	2	1	0.33	Remove	-	-	-	-	-
TOL41	7	2	0	0.56	Revise	98.27	98.61	-0.073	0.708	Removed
TOL42	7	2	0	0.56	Revise	97.88	98.34	-0.062	0.710	Removed
TOL43	7	2	0	0.56	Revise	98.57	97.03	0.041	0.698	Removed
TOL44	6	2	1	0.33	Remove	-	-	-	-	-
TOL45	8	1	0	0.78	Keep	98.49	97.28	0.018	0.700	Removed
TOL46	7	2	0	0.56	Revise	98.42	97.63	-0.006	0.702	Removed
TOL47	8	1	0	0.78	Keep	98.35	98.05	-0.052	0.706	Removed
TOL48	7	2	0	0.56	Revise	98.51	97.19	0.022	0.700	Removed
TOL49	8	1	0	0.78	Keep	98.44	97.46	0.009	0.701	Removed
TOL50	9	0	0	1.00	Keep	98.29	98.27	-0.058	0.706	Removed

Table 2. Testing reliability statistics after item screening

Item	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item–Total Correlation	Cronbach's α if Item Deleted
After item screening: α = .836, 18 items retained				
TOL1	34.04	42.31	0.411	0.829
TOL2	34.02	42.85	0.371	0.831
TOL3	34.04	42.98	0.368	0.831
TOL13	33.96	42.41	0.402	0.830
TOL19	34.97	41.37	0.512	0.823
TOL21	35.2	42.71	0.45	0.827
TOL22	35.12	43.57	0.365	0.831
TOL23	35.35	43.28	0.415	0.829
TOL24	35.34	42.71	0.489	0.825
TOL25	35.29	42.19	0.536	0.823
TOL26	35.24	42.59	0.501	0.825
TOL27	35.34	42.54	0.497	0.825
TOL28	35.33	42.54	0.532	0.824
TOL29	35.01	43.51	0.302	0.835
TOL30	35.05	43.25	0.395	0.830
TOL31	35.04	42.7	0.422	0.828
TOL32	35.11	42.89	0.431	0.828
TOL33	35.08	43.22	0.384	0.830

Table 3. KMO and Bartlett's test of sphericity for the final 18 items (n = 200)

Test	Value
Kaiser–Meyer–Olkin value	0.837
Bartlett's Test of Sphericity — Approx. χ^2	1790.848
df	153
Significance (p)	<0.001

Meyer–Olkin (KMO) was assessed to measure the sampling adequacy (0.837), and was above the recommendation of 0.7, It indicates that inter-item correlation patterns were suitable for factor analysis. Additionally, Bartlett's test was also significant (χ^2 = 1790.848, df = 153, p < .001), it shows that correlation matrix was not just an identity matrix and a common variance is present.

Direct Oblimin rotation was used in Principal Axis Factoring which extracted four factors having eigen values more than 1.0 and explaining a total variance of 67.41%. Factor 1 (eigenvalue = 5.044, 28.02% variance), Factor 2 (eigen value = 3.098, 17.21%), Factor 3 (eigenvalue = 2.730, 15.17%), and Factor 4 (eigen value = 1.262, 7.01%). All communalities exceeded 0.30, and all pattern matrix loadings were more than the 0.50 threshold.

Factor structure and scale interpretation

The rotated pattern matrix revealed a clean four-factor structure with no problematic cross-loadings. The factor inter-correlation matrix indicates a moderate correlation between factors (ranging from 0.10 to 0.52), supporting the use of oblique rotation and confirming that the factors were conceptually distinct and share a common latent construct of wildlife tolerance. Factor 1 representing Adaptive Coexistence Behaviour (6 items: TOL23, TOL27, TOL24, TOL28, TOL25, TOL26), captures respondents' willingness to adopt preventive farming practices and participate in community-level conflict-mitigation efforts. Higher scorers indicate proactive behavioural orientations toward reducing HWC through adaptation rather than exclusion of wildlife. Factor 2 represents Coexistence Acceptance (4 items: TOL1, TOL3, TOL2, TOL13), which reflect fundamental acceptance of wildlife presence and coexistence near agricultural landscapes. Items loaded strongly on this factor,

Table 4. Rotated factor pattern matrix (Principal Axis Factoring, Direct Oblimin rotation; n = 200)

Item	F1 Adaptive Coexistence	F2 Coexistence Acceptance	F3 Conservation Tolerance	F4 Damage & Adaptation Tolerance*	Communality
TOL23	0.917				0.668
TOL27	0.684				0.576
TOL24	0.653				0.508
TOL28	0.637				0.508
TOL25	0.558				0.539
TOL26	0.545				0.572
TOL1		0.884			0.794
TOL3		0.842			0.704
TOL2		0.840			0.701
TOL13		0.792			0.640
TOL29			0.966		0.887
TOL31			0.711		0.523
TOL32			0.664		0.472
TOL30			0.656		0.455
TOL33			0.643		0.427
TOL19				–.750	0.642
TOL21				–.585	0.429
TOL22				–.512	0.416
Eigenvalue	5.044	3.098	2.730	1.262	
% Variance	28.02	17.21	15.17	7.01	
Cumulative %	28.02	45.23	60.40	67.41	

Note: Loadings <0.50 suppressed. (R) = items reverse-scored for Factor 4. Extraction: Principal Axis Factoring; Rotation: Direct Oblimin. Overall α =0.836.

suggesting a stable attitudinal core around –human-wildlife cohabitation. Factor 3 represents Conservation-Oriented Tolerance (5 items: TOL29, TOL31, TOL32, TOL30, TOL33), it shows farmers' broader conservation values, support for continued wildlife conservation despite inconvenience, importance of environmental balance, and responsibility toward future generations. Factor 4 represents Damage and Adaptation Tolerance (3 items: TOL19, TOL21, TOL22), items on this factor originally loaded negatively in the pattern matrix, indicating that scores were inversely related to the general tolerance direction. Following standard psychometric practice, these items were reverse-scored. After reversal, high scores on Factor 4 indicate willingness to accept wildlife-related losses as manageable and readiness to modify farming systems in response to conflict. This factor represents tolerance at the interface of material cost-acceptance and behavioural flexibility. The rotated factor matrix (pattern matrix) is presented in Table 4.

Final selected statements were represented in the table 5 and it is used in the final survey of 200 households residing in the buffer zone of four range in RTR, Uttar Pradesh. Statements were categorised in to different factors according to the results of EFA along with their Cronbach alpha value of each factor.

Tolerance level of households in RTR buffer zones

Normalised scores of the tolerance scores were categorised into three categories, i.e., low tolerance, medium tolerance, and high tolerance level. Tolerance of different households in different ranges was presented in Table 6. Households in the Manikpur I range have the lowest tolerance, as the majority (Low: 42.50%; Medium: 55.00%) of households have a low to medium level of tolerance towards wildlife. Whereas Markundi II has a medium to high level of tolerance (Medium: 61.67%, High: 28.33%). Overall, households residing in the Buffer zones of RTR, Uttar Pradesh, have a low (23.00%) to medium level (59.00%) of tolerance.

Table 6. Tolerance level of households in RTR buffer zones

Range	Low Tolerance (%)	Medium Tolerance (%)	Highly Tolerance (%)
Manikpur I	42.50	55.00	2.50
Manikpur II	23.33	56.67	20.00
Markundi I	22.50	62.50	15.00
Markundi II	10.0	61.67	28.33
Overall	23.00	59.00	18.00

DISCUSSION

The nine experts reviewed the50 items and were analysed using Content Validity Ratio (CVR), resulting in the retention of 43 items, and 7 items were removed due to consistently low expert agreement. The majority of the removed items were affective and ask about the feelings that were removed and can also be observed in other scale construction methodologies (Kansky et al., 2016; Prabex et al. 2025). Items that received consensus or agreement of the experts (CVR = 1.00) were majorly behavioural and experiential acceptance of wildlife presence, participation in mitigation, and coexistence values, suggesting that agricultural wildlife tolerance in buffer-zone contexts is anchored to practical experience rather than emotional disposition. These findings are consistent with the previous researches related to conservation social science, concluding that direct experience with wildlife majorly shapes tolerance than abstract value orientations (Yeshey et al., 2024; Velamuri et al. 2024; Kademani et al., 2025).

The initial Cronbach's alpha of 0.688 with 43 items indicated marginal reliability, which improved substantially to 0.836 following

Table 5. Final Wildlife Tolerance Scale for Buffer Zone Farmers (WTS-BZF): items, factors, and scoring

Item Code	Statement
Factor 1: Adaptive Coexistence Behaviour (6 items, α = 0.82)	
TOL23	I would use preventive measures before resorting to wildlife removal
TOL27	I am willing to participate in community efforts to reduce human–wildlife conflict
TOL24	I prefer coexistence measures rather than removing wildlife from the area
TOL28	I would support village-level wildlife mitigation programs
TOL25	I am willing to spend time protecting crops through non-lethal methods
TOL26	I support solutions that reduce conflict without harming wildlife
Factor 2: Coexistence Acceptance (4 items, α = 0.88)	
TOL1	I accept the presence of wildlife near my village
TOL3	People and livestock should coexist with wildlife in my community
TOL2	I believe humans and wildlife should be able to live side by side
TOL13	I can tolerate occasional agricultural losses caused by wildlife
Factor 3: Conservation-Oriented Tolerance (5 items, α = 0.83)	
TOL29	I would cooperate with local conservation initiatives
TOL31	Wildlife conservation should continue even if some inconvenience is experienced
TOL32	Protecting wildlife is important for maintaining environmental balance
TOL30	Wildlife conflict should be addressed through adaptation rather than elimination
TOL33	Future generations should benefit from maintaining wildlife populations
Factor 4: Damage and Adaptation Tolerance (3 items, α = 0.79)	
TOL19	Wildlife-related losses should be managed rather than eliminated
TOL21	I am willing to make adjustments to my farming practices to accommodate wildlife
TOL22	I am willing to change agricultural practices to reduce wildlife conflict

systematic removal of items with near-zero or negative corrected item–total correlations (CITC). The final 18-item pool exhibited CITC values ranging from 0.302 to 0.536, with no individual item deletion improving the overall alpha, confirming that each retained item contributed unique and coherent variance to the composite tolerance construct. An alpha of 0.836 meets the threshold of 0.80 considered acceptable for social science instruments (Kalkbrenner, 2021; Jahangiry et al., 2025). The iterative item-screening approach used here mirrors the procedures reported by Patra et al. (2026) in their development of a farmer adaptation scale in eastern India, where progressive item removal raised alpha from .65 to .82 across a comparable item pool.

The KMO value of .837 and a significant Bartlett's test ($p < .001$) confirmed strong factorability, and Principal Axis Factoring extracted a theoretically coherent four-factor solution explaining 67.41% of total variance. Factor 1 (Adaptive Coexistence Behaviour; 28.02% variance) emerged as the dominant component, with the highest-loading item being willingness to use preventive measures before resorting to wildlife removal (TOL23 = .917). The primacy of this behavioural orientation factor aligns with the Theory of Planned Behaviour (Islam and Mehidi, 2024), which identifies behavioural intention as the proximal determinant of action — making this dimension the most extension-amenable, as intentions are modifiable through skill-building and community demonstration programmes. Factor 2 (Coexistence Acceptance) reflected fundamental attitudinal acceptance of human–wildlife cohabitation, and the loading of the loss-acceptance item (TOL13 = 0.792) on this factor rather than on the damage-specific Factor 4 — suggests that occasional loss-tolerance is embedded in broader coexistence worldviews in this landscape rather than being experienced as a discrete economic decision (Denryter and Heeren, 2021). Factor 3 (Conservation-Oriented Tolerance) captured biospheric value orientations, with the dominant loading of the cooperation item (TOL29 = 0.966) indicating that conservation efficacy beliefs are a distinct and independent dimension of tolerance (Hobson et al., 2024). Factor 4 (Damage and Adaptation Tolerance) presented negative loadings in the raw pattern matrix, consistent with findings by Kortetmaki et al. (2025) and Sasikumar et al. (2026) who noted that cost-bearing items are frequently interpreted as signalling unfair burden in rural conflict contexts. Reverse-scoring resolved this artefact, yielding a conceptually meaningful dimension representing farmers' capacity to frame losses as manageable and to accept farming-system adaptation.

Application of the WTS-BZF to the full sample revealed a predominantly low-to-medium tolerance distribution (23.00% low; 59.00% medium; 18.00% high), consistent with previous HWC research from South Asian tiger reserve landscapes documenting pervasive negative attitudes among smallholder farming communities (Agnihotri et al., 2021; Warrier, 2019). Range-level variation was notable: Manikpur I recorded the highest proportion of low-tolerance households (42.50%), which may reflect its smaller spatial area and correspondingly higher habitat-edge density and conflict frequency, as greater proximity to wildlife habitats has been linked to suppressed tolerance through negative reinforcement (Harris et al. 2023; Iqbal et al., 2021). In contrast, Markundi II showed the lowest low-tolerance proportion (10.00%) and the highest medium-to-high tolerance, potentially attributable to greater physical buffering from the reserve core. The majority of households across all ranges are in the medium-tolerance level which identifies a priority target segment for agricultural extension and individuals in intermediate attitudinal zones are consistently found to be most responsive to information-based and community-norm interventions (Junca et al., 2023; Meena et al., 2022). The scale's ability to detect meaningful sub-range variation in tolerance further confirms its discriminant validity and suitability as a diagnostic tool for range-specific extension planning within tiger reserve governance structures.

CONCLUSION

The Wildlife Tolerance Scale for Buffer Zone Farmers (WTS-BZF) is a psychometrically validated scale, consisting of18 items, and responses can be collected on a 5-point Likert instrument for measuring agricultural human–wildlife conflict tolerance among buffer-zone households. Developed through rigorous content validation (CVR with nine experts), systematic pilot-phase item screening (Cronbach's $\alpha = 0.836$ post-refinement), and Exploratory Factor Analysis on 200 households of Ranipur Tiger Reserve, Uttar Pradesh. The scale yields four interpretable and internally consistent dimensions namely Adaptive Coexistence Behaviour, Coexistence Acceptance, Conservation-Oriented Tolerance, and Damage and Adaptation Tolerance. Together, these dimensions explain 67.41% of total variance in wildlife tolerance. The WTS-BZF addresses a significant methodological gap in South Asian human–wildlife conflict research and provides extension workers, conservation planners, and programme evaluators with a ready-to-use, context-validated tool for assessing tolerance baselines, monitoring intervention outcomes, and designing community-level coexistence programmes in tiger reserve buffer zones across India.

DECLARATIONS

Ethics statement: The study was conducted in accordance with ethical research standards. Participation was voluntary, and informed consent was obtained from all respondents. The confidentiality and anonymity of participants were strictly maintained throughout the research process.

Competing interests: The authors declare that there are no conflicts of interest regarding the publication of this paper.

Data availability statement: Data is available upon request from the first author as well as co-authors.

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Research Tool

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A Novel Framework for Constructing a Robust Octa-Dimensional Climate-Smart Agriculture Index

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HIGHLIGHTS

- An Octa-dimensional Climate-Smart Agriculture Index (ODCSAI) comprising 47 indicators across eight dimensions was developed and content validated.
- The Alfares and Duffuaa model ensures a weight of 100 for the top-ranked dimension, eliminating value dilution in index construction.
- Crop Smart emerged as the most critical CSA dimension with the highest cardinal weight (W = 93.73).
- Supplementary reliability triangulation using Spearman-Brown (0.872), Guttman split-half (0.829), and Cronbach's alpha (0.848) confirmed internally stable scoring.

ARTICLE INFO

Keywords: Climate change, Climate-smart agriculture, Cronbach's alpha, Index, Reliability, Spearman-brown.

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ABSTRACT

Escalating climate variability induced risks in agriculture dependent economies necessitated a standardised composite index to measure farm level adoption of Climate-Smart Agriculture (CSA) practices. The study, conducted in 2024, developed the Octa-dimensional Climate-Smart Agriculture Index (ODCSAI) by combining the established cardinal weight assignment model of Alfares and Duffuaa with the min-max normalisation protocol of the Food and Agriculture Organisation (FAO). Eight CSA dimensions viz. Crop Smart, Weather Smart, Water Smart, Carbon Smart, Energy Smart, Nutrient Smart, Knowledge Smart, and Market Smart were delineated through a structured review of seven CSA frameworks and operationalised using 47 indicators. Ordinal rankings elicited from 120 subject matter experts were converted into cardinal weights, with Crop Smart registering the highest weight (W = 93.73), followed by Weather Smart (W = 87.20) and Water Smart (W = 84.17), while Market Smart recorded the lowest (W = 48.03). Content validity was established using a six-member expert panel (S-CVI = 0.935), and psychometric reliability, assessed on 50 farmers across two Climate Smart Villages in Bihar, was triangulated through the Spearman-Brown coefficient (0.872), Guttman split-half coefficient (0.829), and Cronbach's alpha (0.848). The ODCSAI thus constituted a content-validated instrument for quantifying farm-level CSA adoption.

INTRODUCTION

Agriculture in climate dependent economies faces intensifying threats from erratic weather patterns, prolonged droughts, and flood events, all of which jeopardise long term food security and rural livelihoods (Raghuvanshi et al., 2020; Phebe et al., 2024). Climate-Smart Agriculture (CSA) offers a comprehensive, evidence-based strategy to simultaneously enhance agricultural productivity,

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strengthen adaptive capacity, and reduce greenhouse gas emissions (Borah et al., 2025). As CSA interventions are implemented at scale across diverse agro-ecological settings, the ability to assess and compare the climate smartness of individual farmers and farming systems has become increasingly critical for guiding policy, targeting extension efforts, and evaluating the outcomes of completed projects (Meena et al., 2023; Kumar & Saxena, 2024; Pathak et al., 2024). CSA consists of multiple interrelated dimensions viz., crop management, water use, carbon sequestration, energy efficiency, market integration, and knowledge dissemination that differ in their relative importance across contexts, making a multidimensional, weighted measurement approach essential for meaningful cross site comparison (Shitu et al., 2018a; Shitu et al., 2018b; Harikrishna et al., 2019; Chouksey et al., 2021).

Although composite measures of farm-level climate smartness have begun to appear (Singh et al., 2024), they typically derive dimension weights through schemes such as the analytic hierarchy process that dilute the proportional value of the highest-ranked dimension, leaving a need for a transparent, proportionally weighted tool capable of quantifying farm-level CSA adoption in a standardised and reproducible manner. The construction of composite indices to operationalise complex socio-agricultural constructs is well established in development research. Environmental sustainability (Sands et al., 2000), food and human security (Carolan, 2012), livelihood vulnerability (Madhuri et al., 2014), rural development (Michalek & Zarnekow, 2012), and sustainable livelihood security (Singh & Hiremath, 2010) have each been captured through multidimensional index frameworks. Despite this precedent, a rigorous, replicable, and universally adaptable methodology for index construction remains elusive, and several prevailing approaches exhibit inherent structural limitations that compromise the validity and comparability of the resulting scores (Lal et al., 2017).

Garrett's (1979) ranking technique, for instance, restricts the maximum attainable weight of the top ranked dimension to 78 rather than 100 in a seven-criterion framework, systematically undervaluing the most critical element. The method also requires field researchers to carry printed conversion tables, posing a logistical inconvenience. Alkire and Foster's (2011) widely adopted Multidimensional Poverty Index methodology, though theoretically grounded, excludes households with composite deprivation scores below one-third from the final computation, resulting in structural under coverage of the target population. Collectively, these limitations reveal the need for an index construction approach that is computationally transparent, assigns full proportional value to the highest ranked criterion, and incorporates all respondents irrespective of their overall score. It is posited that adapting the Alfares and Duffuaa (2009) cardinal weighting model in conjunction with the FAO min-max normalisation protocol provides a transparent and proportional basis for constructing a multidimensional CSA index, one that assigns full value to the highest-ranked dimension and retains all respondents and that the resulting instrument can be shown to be internally reliable. The contribution of this study lies in application and validation rather than in the derivation of new weighting mathematics. First, it operationalises an established weighting-normalisation confluence, previously applied to livelihood security (Lal et al., 2017), for measuring farm-level Climate-Smart Agriculture adoption. In contrast to existing farm-level CSA indices that derive dimension weights through the analytic hierarchy process (Singh et al., 2024), the Alfares–Duffuaa formulation assigns a full weight of 100 to the top-ranked dimension, thereby avoiding value dilution. Second, it synthesises eight CSA dimensions from a review of seven frameworks and renders them measurable through 47 scored indicators, yielding a concrete and reusable assessment tool. Third, it subjects the resulting index to a three-way reliability triangulation (Spearman–Brown, Guttman split-half and Cronbach's alpha), supplemented by ANOVA with Cochran's test, thereby providing psychometric evidence that earlier single-coefficient index studies have often omitted.

METHODOLOGY

The present study, conducted in 2024, delineated eight Climate-Smart Agriculture (CSA) dimensions viz., Crop Smart, Weather Smart, Water Smart, Carbon Smart, Energy Smart, Nutrient Smart, Knowledge Smart and Market Smart through a structured review of CSA frameworks. A structured literature review was conducted in Scopus (2018–2023), restricted to the title, abstract, and keyword fields, using the query: ("Climate Smart Agriculture" OR "Climate-Smart Agriculture" OR CSA) AND ("CSA Index" OR "Composite Index" OR indicator OR framework OR metric) AND (dimension OR pillar OR component). This was supplemented by backward citation searching (snowballing) of the retrieved records. Of the 87 records screened, seven frameworks (Appendix Table 1) met the inclusion criterion i.e., decomposition of CSA into discrete, named dimensions that are operationalisable through measurable indicators. Sources specifying no such structure, or describing CSA goals (e.g., adaptive capacity, food and nutrition security, mitigation) rather than measurable practice domains, were excluded. The retained set spanned international (Aggarwal et al., 2018; Anuga et al., 2019; Ghimire et al., 2022; Antwi-Agyei et al., 2023) and Indian (Bhattacharyya et al., 2020; Singh et al., 2021; Chakraborty et al., 2023) contexts. Rather than adopting any single scheme, the eight dimensions were synthesised across the seven frameworks and synonymous labels were matched (e.g., 'Nitrogen Smart' with 'Nutrient Smart'; 'Seed/Breed' and 'Planting' with 'Crop Smart'), composite labels were disaggregated where treated separately (e.g., 'Carbon/Nutrient Smart', 'Institutional/Market Smart'), and outcome-oriented categories were excluded as non-operationalisable, yielding eight unique dimensions recurring across the literature. A standardised questionnaire soliciting ordinal ranks from 1 to 8 was administered to 138 subject-matter experts, of whom 120 responded (response rate 87.0%); these were randomly selected extension scientists, subject-matter specialists, agronomists and research scholars from agricultural universities, KVKs and ICAR institutes across India.

Ordinal ranks were converted into cardinal weights using the Alfares and Duffuaa (2009) model, adopted here in preference to earlier rank-based weight-approximation methods (Stillwell et al., 1981; Barron, 1992; Lootsma, 1999) because it assigns full proportional value to the top-ranked criterion (Lal et al., 2017). The slope (Sn) declines non-linearly with the number of criteria (n), derived by least-squares regression as:

$S_n = 3.19514 + 37.75756 / n$

which gave Sn = 7.914835 for n = 8. With a weight of 100 assigned to the first-ranked dimension, the weight of a dimension ranked r is:

$W_{r,n} = 100 - S_n (r - 1),\ 1 \le r \le n$

where $W_{r,n}$ is the cardinal weight at rank r, S_n the slope constant, and r and n integers. The aggregate weight of dimension d was obtained as the frequency-weighted mean of the rank weights:

$W_d = \Sigma (W_{r,n} f_{r,d}) / \Sigma f_{r,d}$

where $f_{r,d}$ is the number of experts assigning rank r to dimension d, the denominator equalling 120.

As the indicators used different measurement units, each was standardised to a 0 to 1 scale by min-max normalisation (Sullivan et al., 2010):

$Z_i = (X_i - X_{min}) / (X_{max} - X_{min})$

where X_i is the observed value of indicator i, and X_{min} and X_{max} its minimum and maximum attainable values. For each respondent j, each dimension score (Zij) was computed as the mean of the normalised values (Zi) of its constituent indicators. The composite score of respondent j was the weighted mean of the normalised dimension scores (Sullivan et al., 2010):

$CSA_j = \Sigma (W_i Z_{ij}) / \Sigma W_i$

where W_i is the cardinal weight of dimension i and Z_{ij} its normalised score for respondent j.

Expanded across the eight dimensions, this becomes:

$$CSA_j = (W_{CrS} \cdot CrS_j + W_{WeS} \cdot WeS_j + W_{WaS} \cdot WaS_j + W_{CaS} \cdot CaS_j + W_{ES} \cdot ES_j + W_{NS} \cdot NS_j + W_{KS} \cdot KS_j + W_{MS} \cdot MS_j) / (W_{CrS} + W_{WeS} + W_{WaS} + W_{CaS} + W_{ES} + W_{NS} + W_{KS} + W_{MS})$$

Where, *CrS*, *WeS*, *WaS*, *CaS*, *ES*, *NS*, *KS* and *MS* are the normalised scores of Crop Smart, Weather Smart, Water Smart, Carbon Smart, Energy Smart, Nutrient Smart, Knowledge Smart and Market Smart, respectively, for respondent *j*, and the corresponding *W* terms their cardinal weights.

Content validity was established before reliability testing using Lynn's (1986) method. Six experts from Agricultural Extension and Agronomy rated an initial pool of 52 indicators for relevance on a four-point scale (1 = not relevant to 4 = highly relevant); five items were removed on their judgement, retaining 47 indicators. The item-level content validity index (I-CVI) was the proportion of experts rating an indicator 3 or 4, and the instrument-level index their mean:

S-CVI = Σ(I-CVI) / *n*

where n is the number of indicators. An I-CVI of 0.83 or above (Lynn, 1986) and an S-CVI of 0.90 or above (Polit & Beck, 2006) denoted item retention and excellent content validity, respectively.

Reliability was assessed on 50 randomly drawn farmers (25 each from Climate Smart Village (CSV) Phulhara, Samastipur and CSV Ojhaul, Darbhanga, Bihar) using three internal-consistency coefficients. Split-half reliability used the Spearman-Brown formula (Spearman, 1910; Brown, 1910):

$r_{SB} = 2r_{hh} / (1 + r_{hh})$

where r_{hh} is the Pearson correlation between the two halves. The Guttman split-half coefficient was computed in SPSS (Version 27), and Cronbach's alpha (Cronbach, 1951) was also employed. As the index is a multidimensional composite, its full-scale alpha indexes overall internal consistency rather than one-dimensionality (Schmitt, 1996). The 47 items were split into Part 1 (S1 to S24) and Part 2 (S25 to S47), the unequal division reflecting the odd item total. Johanson and Brooks (2010) consider 30 respondents adequate for pilot reliability estimation, which this sample exceeded; the pilot used non-sample villages to avoid contaminating the main study population.

RESULTS

An analysis of Table 1 indicated that among the eight dimensions of the CSA index, Crop Smart possessed the highest weightage of 93.73 with four indicators, followed by Weather Smart at 87.20 with six indicators, Water Smart at 84.17 with nine indicators, Carbon Smart at 77.57 with five indicators, Energy Smart at 67.62 with five indicators, Nutrient Smart at 63.92 with five indicators, Knowledge Smart at 56.14 with seven indicators, and Market Smart at 48.03 with six indicators. Notably, a dimension ranked first is assigned a weight of 100, ensuring no loss of value.

Validity and reliability statistics of the indicator statements

Content validity was established following Lynn's (1986) methodology. Item-level content validity indices (I-CVIs) for the

Table 1. Cardinal weights of CSA index dimensions based on ordinal rankings (n=120)

Ranks	CrS	WeS	WaS	CaS	ES	NS	KS	MS	$W_{r,n}$
1	83	19	3	9	0	5	1	0	100.000
2	15	68	17	6	3	3	5	3	92.085
3	7	12	86	8	1	3	2	1	84.170
4	4	6	10	82	9	4	1	4	76.255
5	4	3	0	9	89	6	8	1	68.341
6	5	3	3	3	8	92	6	0	60.426
7	1	6	1	0	7	7	88	10	52.511
8	1	3	0	3	3	0	9	101	44.596
Σf	120	120	120	120	120	120	120	120	
$\Sigma W_{r,n}$ f	11248.09	10464.52	10100.44	9308.96	8113.82	7670.59	6736.63	5763.11	
1/Σf	0.00833	0.00833	0.00833	0.00833	0.00833	0.00833	0.00833	0.00833	
W	93.73	87.20	84.17	77.57	67.62	63.92	56.14	48.03	

W= Weightage; S_n = 7.914835; M_c (Mean of W) = 72.2980775; Standard Error for M_c = 5.658202049; f=frequency

Table 2. Reliability statistics of the indicator statements

Cronbach's α	P 1	Value	0.565
		Total Items	24
	P 2	Value	0.817
		Total Items	23
		Grand total	47
Cronbach's α value			0.848
Cronbach's α based on standardised items			0.863
Correlation b/w forms			0.772
Spearman-Brown Coefficient		Equal Length	0.872
		Unequal Length	0.872
Guttman Split-Half Coefficient			0.829
ANOVA with Cochran's Test		420.837	0.000

a. The items are: S1, S2, S3…S24.
b. The items are: S25, S26, S27…S47.

initial 52 indicators ranged from 0.667 to 1.00. Five indicators failed to meet the retention criterion (I-CVI ≥ 0.83 for six experts) and were therefore removed, yielding a final set of 47 indicators (Appendix Table 2). The scale-level content validity index (S-CVI) was 0.935, exceeding the 0.90 benchmark indicative of excellent content validity (Polit & Beck, 2006).

Beyond content validity, the internal consistency of the 47-item set as administered was examined as a supplementary check on score stability. As evident from Table 2, the index was divided into two halves of 24 (Part 1) and 23 (Part 2) items. The Pearson correlation was 0.772, which on Spearman-Brown correction yielded 0.872 for both equal and unequal length forms; the Guttman split-half coefficient was 0.829, with both estimates significant at the 1% level. Cronbach's alpha for the full 47-item scale was 0.848, within the 'good' range per George and Mallery (2003), and 0.863 for standardised items. Dimension-wise Cronbach's alpha (α) ranged from 0.511 to 0.758 (Weather Smart = 0.511, Crop Smart = 0.571, Water Smart = 0.606, Knowledge Smart = 0.620, Energy Smart = 0.657, Nutrient Smart = 0.669, Market Smart = 0.751, Carbon Smart = 0.758), and the part-wise estimates were 0.565 (Part 1) and 0.817 (Part 2). These subscale values are necessarily modest, as each dimension comprises only four to nine largely binary indicators, for which alpha is mathematically depressed (Cortina, 1993; Tavakol & Dennick, 2011). Because the dimensions form a composite that defines, rather than reflects, climate-smart adoption, internal consistency is not the defining quality criterion for the index, and high within-dimension inter-item correlation is neither expected nor required. Content validity accordingly carries the principal evidential weight, with criterion and construct validation identified as the next stage. The coefficients are reported here for completeness and for comparability with extension instruments that conventionally report them. Their close agreement, supported by a significant ANOVA with Cochran's test ($F = 420.837$, $p < 0.01$), indicates that the item set as administered yields internally stable scores.

DISCUSSION

Crop Smart received the highest cardinal weight among the eight dimensions, a result consistent with the centrality of crop management in climate-adaptive strategies (Sain et al., 2017; FAO, 2013). In the rice-wheat systems of Bihar and the wider Indo-Gangetic Plains, the crop is the most immediate point of climate exposure and the most readily adjusted, through stress-tolerant varieties, diversification and improved cropping systems, upon which water, nutrient and energy management subsequently build. The ranking, however, reflects expert priority rather than demonstrated field performance or actual farmer adoption, particularly as the panel was dominated by agronomists and extension scientists who may favour the practices closest to their own training (Ghanghas et al., 2015).

The weights are also conditioned by the study setting. Climate-smart agriculture is highly context-specific, and the practices that matter most differ across farming systems and agro-ecological zones (Tabe-Ojong et al., 2024a); a panel situated in a water-scarce or flood-prone region might therefore rank the dimensions differently. The weights reported here are accordingly specific to this setting rather than fixed. This is a property of the method rather than a limitation, since the Alfares and Duffuaa approach permits the weights to be re-estimated for any region through a fresh round of expert ranking, allowing the structure of the index to transfer even where the weights themselves cannot.

The comparatively low weights assigned to Knowledge Smart and Market Smart merit attention, as they sit at odds with the wider literature. These dimensions capture the enabling conditions, namely information access, farmer organisation, value addition and market linkage, that many studies identify as principal barriers to adopting and scaling climate-smart agriculture (Tabe-Ojong et al., 2024b; Agyekum et al., 2024). In India, Mishra et al. (2026) report that limited knowledge and skills, weak finances and insecure land tenure rank among the most common barriers to adoption, and that cooperative membership lowers them. The low weights may thus reflect a tendency among technical experts to prioritise biophysical practices over these institutional and market dimensions.

Reliability was examined through three complementary coefficients. The Spearman-Brown coefficient corrects the underestimation arising from halving a scale, the Guttman split-half coefficient provides a conservative lower-bound estimate, and Cronbach's alpha measures overall internal consistency across all 47 items; their close agreement, together with the significance of the Spearman-Brown and Guttman values at the 1% level, indicates that the result does not depend on any single test. The estimates are consistent with comparable extension instruments. Shukla et al. (2024) reported an alpha of 0.801 and a Spearman-Brown of 0.828 for the Standardised Information Need Index, Panigrahi et al. (2024) a split-half of 0.81, a Spearman-Brown of 0.89 and an alpha of 0.83 for an agripreneurial performance scale, and Sahu et al. (2026), using a similar non-sample-village design, an alpha of 0.951 and a Spearman-Brown of 0.936. As Schmitt (1996) cautions, alpha alone is insufficient; the split-half coefficients and the significant ANOVA with Cochran's test are therefore reported alongside it as supplementary checks.

In practical terms, the index offers extension functionaries a means to identify the dimensions on which a farmer or village is weak, to compare households and locations, and to monitor and evaluate climate-smart agriculture interventions. Its limitations are nonetheless acknowledged, the weights are expert-derived and

context-bound, and reliability was assessed on only 50 farmers in a single state, warranting confirmation on larger and more diverse samples. As demonstrated for other extension scales (Meethal & Thomas, 2024), exploratory factor analysis with convergent and criterion validation on a larger sample represents the natural next step.

CONCLUSION

By combining the established Alfares and Duffuaa weighting model with the Food and Agriculture Organisation min-max normalisation protocol, this study delivers a content-validated and reliability-tested instrument, the Octa-dimensional Climate-Smart Agriculture Index, for quantifying farm-level Climate Smart Agriculture adoption. The adopted weighting approach retains a full weight of one hundred for the highest-ranked dimension, avoiding the value dilution inherent both in rank-based alternatives such as Garrett's technique and in the analytic-hierarchy weighting used by recent farm-level CSA indices. The resulting eight-dimensional index, comprising forty-seven indicators and supported by content validity and triangulated reliability, constitutes a standardised tool for assessing the climate-smart status of farm households. Crop-related practices emerged as the foremost priority among the experts consulted, underscoring the centrality of crop management in climate-adaptive strategies. The index provides a transferable structure that remains adaptable across regions through context-specific alterations, offering a practical resource for policymakers, extension workers, and researchers advancing resilient and sustainable agriculture.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the 120 judges who contributed in assigning ranks to the proposed dimensions, the 50 farmers from two non-sample villages during the course of the data collection and the 6 judges who contributed in content validity.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors declare that during the preparation of this work, they thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication

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APPENDIX

Table 1. Climate Smart Agriculture dimensions as suggested by various researchers

S.No.	Name of the researcher(s)	No. of dimensions	Name of the dimensions	
1	Aggarwal et al. (2018)	5	1) 'Weather Smart' 2) 'Water Smart' 3) 'Seed/Breed Smart' 4) 'Carbon/Nutrient Smart' 5) 'Institutional/Market Smart'	
2	Anuga et al. (2019)	6	1) 'Weather Smart' 2) 'Water Smart' 3) 'Carbon Smart' 4) 'Nitrogen Smart' 5) 'Energy Smart' 6) 'Knowledge Smart'	
3	Bhattacharya et al. (2020)	6	1) 'Weather smart' 2) 'Water smart' 3) 'Crop smart' 4) 'Nutrient smart 5) 'Carbon/energy smart' 6) 'Institution/Knowledge smart.'	
4	Singh et al. (2021)	6	1) 'Community Smart'	i) 'Community Service Centre' ii) 'Seed Bank' iii) 'Machine Bank' iv) 'Fodder Bank'
			2) 'Knowledge Smart'	i) 'Farmer-Scientist Interface' ii) 'Weather Smart'
			3) 'Input Smart'	i) 'Water Smart' ii) 'Nutrient Smart' iii) 'Energy Smart' iv) 'Carbon Smart'
			4) 'Adaptive Capacity' 5) 'Food and Nutrition Security' 6) 'Mitigation'	
5	Ghimire et al. (2022)	6	1) 'Nutrient Smart' 2) 'Water Smart' 3) 'Crop Smart' 4) 'Information Smart' 5) 'Energy Smart' 6) 'Future Smart'	

Appendix Table 1 contd...

S.No.	Name of the researcher(s)	No. of dimensions	Name of the dimensions
6	Antwi-Agyei et al. (2023)	7	1) 'Weather Smart' 2) 'Water Smart' 3) 'Carbon Smart' 4) 'Nitrogen Smart' 5) 'Energy Smart' 6) 'Knowledge Smart' 7) 'Planting Smart'
7	Chakraborty et al. (2023)	6	1) 'Weather Smart' 2) 'Water Smart' 3) 'Carbon Smart' 4) 'Nitrogen Smart' 5) 'Energy Smart' 6) 'Knowledge Smart'

Table 2. Indicator Statements to measure Climate Smart level of farmers

	Indicators	Responses from farmers	I-CVI
1) Weather Smart	Draw on personal experience to anticipate weather conditions.	Yes= 1; No= 0	1
	Usage of TV/Mobile phone/Internet/Radio for weather information	Phone/ Internet= 1 TV/Radio= 0.5 No weather information= 0	0.83
	Received training/education on how to access weather information	Yes=1; No= 0	1
	Obtained weather updates via the Community Information Centre.	Yes= 1; No= 0	1
	Beneficiary of Weather Index-Based Insurance (IBI)	Yes= 1; No= 0	0.83
	Weather-related information received from University/Krishi Vigyan Kendra (KVK)	Regularly= 1 Occasionally= 0.5 Never= 0	1
2) Water Smart	Practice of mulching to reduce excessive use of water	Yes=1; No= 0	1
	Reduce water wastage while irrigating fields	Very efficient=1 Moderately efficient= 0.5 Inefficient= 0	0.83
	Rainwater harvesting on the farm	Yes= 1; No= 0	1
	Direct Seeded Rice (DSR)	Yes = 1; No= 0	1
	Raised bed planting of major crops (Maize, Pigeon Pea and Wheat)	3/3 crops= 1 2/3 crops= 0.67 1/3 crops= 0.33 0/3 crops= 0	1
	Laser land levelling	Once in 2-3yrs= 1 Once in 4-5yrs= 0.67 Once in >5yrs= 0.33 Not at all= 0	0.83
	Alternate wetting/drying irrigation in rice	Yes= 1; No= 0	1
	Field bunding in rice	Yes= 1; No= 0	0.83
	Community irrigation	Yes= 1; No= 0	1
3) Carbon Smart	Optimum utilisation of equipment on the farm (minimum tillage)	Optimum = 1 Sub-optimum= 0.5 Poor utilisation= 0	0.83
	Use plants and animal manure on my farm (Organic manuring)	Yes= 1; No= 0	1
	Plant trees in and around the farm (Agro-forestry)	Yes= 1; No= 0	1
	No tillage	Yes= 1; No= 0	0.83
	Residue management	Yes= 1; No= 0	0.83
4) Nutrient Smart	Legume integration	Yes= 1; No= 0	1
	Calculate the exact dosage of fertiliser or manure needed at the time of application.	Accurate= 1 Approximate= 0.5 Uncalculated= 0	1

Appendix Table 2 contd..

	Indicators	Responses from farmers	I-CVI
	Customise nutrient application according to soil type for each field, using decision-support tools like Nutrient Expert.	Yes= 1; No= 0	0.83
	Use Leaf Colour Chart	Yes= 1; No= 0	1
	Use Green seeker (NDVI sensor) to monitor the Vegetative Index	Yes= 1; No= 0	1
5) Energy Smart	Use of fuel-efficient farm equipment/vehicles	Very efficient= 1 Moderately efficient= 0.67 Less efficient= 0.33 Inefficient= 0	0.83
	Composting of residues after harvesting	Yes= 1; No= 0	1
	Convert residue into bioenergy	Yes= 1; No= 0	1
	Use solar-powered equipment in farming	Yes= 1; No= 0	1
	Eliminate/Reduce Puddling in Rice	Eliminate= 1 Reduce= 0.5 Puddling= 0	0.83
6) Crop Smart	Stress- tolerant varieties (Drought/Flood/ Nutrient stress etc)	Yes= 1; No= 0	1
	Input-efficient varieties	Yes= 1; No= 0	0.83
	Cropping system optimisation	Multiple cropping/ Intercropping/ Crop rotation/ Relay cropping = 1 Monocropping= 0	1
	Diversification of crops	Yes= 1; No= 0	0.83
7) Knowledge / Institutional Smart	Engage in personal information sharing with peers (farmer-to-farmer learning).	Yes= 1; No= 0	1
	Belong to farmer associations	Yes= 1; No= 0	1
	Save seeds for the next season or unexpected situations using a seed storage system.	Yes= 1; No= 0	0.83
	Empowering women by incorporating them into the knowledge pool.	Yes= 1; No= 0	0.83
	Use of ICT tools for information gathering	Yes= 1; No= 0	1
	Attended Capacity development programmes	Yes= 1; No= 0	1
	Access to Custom Hiring Centres (CHCs)	Yes= 1; No= 0	1
8) Market Smart	Ability to conduct Market research and analysis	Yes= 1; No= 0	0.83
	Production of Value-added products	Yes= 1; No= 0	1
	Supply chain integration (to reduce middlemen)	Elimination= 1 Reduction= 0.5 No elimination/reduction= 0	0.83
	Flexibility and adaptability	Yes= 1; No= 0	1
	Collaboration and networking through Farmer Producer Organisations (FPOs)	Yes= 1; No= 0	0.83
	Obtain information on market prices for crops and agricultural inputs.	Proper information= 1 Partial information= 0.5 No information= 0	1

Research Note

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Constraints in Accessing Services of Cooperative Societies: A Garrett Ranking-Based Study

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HIGHLIGHTS

- Timely availability of inputs was the most critical constraint faced by farmers.
- Credit recovery issues and unclear regulations significantly affect cooperative functioning.
- Service quality and procedural complexity are more important than labour and technical constraints.

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ABSTRACT

Cooperative societies play a vital role in promoting agricultural development by providing farmers with access to credit, inputs, and other essential services. However, farmers often face obstacles in effectively using these services. This study was conducted in the Shahjahanpur district of Uttar Pradesh 2024 to identify the primary challenges farmers encounter when accessing cooperative society services and to gather their recommendations for improvement. A total of 120 farmers were randomly selected from 2 blocks and 12 villages, and data were collected through a structured interview schedule. Garrett's Ranking Technique was used to analyse and prioritize constraints and suggestions based on farmers' perceptions. The findings indicated that the availability of inputs, slow loan recovery, and the absence of clear laws or regulations were key issues. Moreover, complex procedures, weak management, and poor-quality inputs also hinder effective participation in cooperative activities. Farmers suggested timely delivery of inputs, increased technical and marketing support, and better-quality seeds and fertilizers to improve the functioning of cooperative societies. Strengthening management practices and enhancing service delivery are crucial for increasing farmers' participation and ensuring the successful operation of cooperative institutions.

INTRODUCTION

Cooperative societies are widely promoted as essential institutional tools for rural development, poverty alleviation, and smallholder empowerment. They provide members with access to credit, farm inputs, extension services, storage, processing, marketing, and training, enabling resource-poor farmers to obtain services they could not access individually (Kehinde & Ogundeji, 2022; Chaudhary et al., 2021; Ubana et al., 2019; Uloh et al., 2023). By pooling resources and strengthening collective bargaining power, cooperatives can boost productivity, income, and market access, especially in regions that rely heavily on agriculture (Kehinde &

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Ogundeji, 2022; Msosa, 2022; Kpernyam Linda Nadoo, 2025). Despite this potential, members often face significant barriers to accessing cooperative services, limiting both participation and impact. Studies from Nigeria, India, and South Asia identify common obstacles, including inadequate capital and weak financial capacity within cooperatives, which result in insufficient or delayed credit, low loan limits, and a narrow range of financial products (Ume et al., 2022; Singh et al., 2023; Ubandoma et al., 2025; Onah et al., 2025). Organizational and governance issues, including poor leadership, corruption, weak supervision, and a lack of cooperative education, further undermine service delivery and member trust, discouraging active participation and long-term commitment (Onah et al., 2025; Idris, 2024; Ubana et al., 2019; Ubandoma et al., 2025).

Infrastructure and institutional environments also limit access. High transportation costs, poor road conditions, distant service points, and limited extension services reduce the effective availability of inputs, training, and government support programs for cooperative members (Ubana et al., 2019; Kobba et al., 2020; Kumar et al., 2020; Uloh et al., 2023; Ubandoma et al., 2025). Regulatory and policy frameworks may impose burdensome procedures, political interference, or inadequate assistance, restricting cooperatives' ability to expand services and integrate into formal financial and input markets (Onah et al., 2025; Idris, 2024; Uloh et al., 2023). Socio-cultural factors, such as mistrust, low member commitment, conflicts of interest, and gendered barriers, add another layer of difficulty in accessing and effectively utilizing available services (Ubana et al., 2019; Ubandoma et al., 2025; Msosa, 2022). Understanding these complex constraints is essential because evidence shows that simultaneous access to credit and cooperative services significantly increases farm productivity compared with having either one alone or neither (Kehinde & Ogundeji, 2022). A targeted analysis of the financial, organizational, infrastructural, and sociocultural barriers to service access can therefore provide a foundation for policy and institutional reforms that support cooperative societies as tools for inclusive development. The study examines the challenges farmers face in accessing cooperative societies to enhance the effectiveness of these institutions. Cooperative societies are crucial to strengthening rural livelihoods by providing farmers with access to credit, agricultural inputs, and technical support.

METHODOLOGY

The study was conducted in Shahjahanpur district, Uttar Pradesh, which was purposively selected for its dense network of Primary Agricultural Credit Societies and the Shahjahanpur District Cooperative Bank Limited. It also serves as an institutional hub, with the U.P. Council of Sugarcane Research and the KRIBHCO fertilizer plant, creating a unique combination of scientific research and cooperative-led extension services, which is the core of my study. A total of 120 cooperative members were randomly selected from 2 blocks and 12 villages as respondents, ensuring that each had availed at least one cooperative service during the preceding three years. The research followed a descriptive design to identify the major constraints farmers faced in accessing cooperative society services and to obtain their suggestions for improvement. The Garrett ranking technique was used to analyze and prioritize the identified constraints. Respondents rated 20 identified constraints on a scale from 1 (least severe) to 5 (most severe) to assess their severity. The challenges faced by respondents are not isolated; they are multidimensional. These were categorized into financial, governance, procedural, infrastructural, and human capital constraints to show that, while societies had the infrastructure, their effectiveness was hindered by complexity and a gap in technical extension services.

RESULTS

The perceived constraints respondents faced in accessing cooperative society services were assessed using the Garrett ranking technique. Table 1 presents the total Garrett scores, mean scores, and corresponding ranks, illustrating the relative severity of constraints experienced by respondents. The analysis highlights the major issues farmers encounter when accessing cooperative society services, including institutional, procedural, and service-related barriers. The ranking of constraints provides a clear understanding of the most critical problems affecting the utilization of cooperative society services. This analysis helps identify priority areas that require attention to improve the efficiency and accessibility of cooperative society services for farmers.

DISCUSSION

In Table 1, "inputs are not available at the right time" emerged as the most serious constraint, with a mean Garrett score of 87.76 and a total Garrett score of 10531.20, ranking it first. This indicates that, according to respondents, timely input supply is more important than nearly every other aspect of the cooperative's operation. This is consistent with previous research that found delayed seed and fertilizer supplies to be a significant constraint on output (Kumar et al., 2020; Sabu & Roy, 2024). The second most important constraint was "slow recovery of loan" (mean 83.33, total 9999.60, Rank II). However, this may seem unusual at first. Farmers frequently view a sluggish recovery as a sign of a complicated payback process, frequent visits, and fines, which cause uncertainty and psychological stress (Gautam et al., 2014; Verma & Kumawat, 2020). Their planning remains complicated by the challenges of obtaining new credit while loan accounts remain unpaid (Kumar et al., 2020). "Unavailability of law" received Rank III with a mean Garrett score of 81.50 and a total Garrett score of 9780.00, demonstrating that members suspect the legal and regulatory framework associated with cooperative operations is either lacking, unclear, or improperly conveyed to them (Ao & Jamir, 2020; Sabu & Roy, 2024). The absence of clear legislation may lead to arbitrary conclusions and inadequate accountability, undermining public confidence in the institution (Kumar and Nain 2012; Das et al., 2014). The constraints "lack of quality fertilizers" (mean 79.83, Rank IV) and "procedures and policies difficult to understand by common people" (mean 75.17, Rank V) emphasize once more that members are concerned about quality and procedural complexity in addition to quantity and price (Krishna et al., 2024; Verma & Kumawat, 2020). Farmers who are unfamiliar with the regulations sometimes rely too heavily on employees, which can lead to abuse or favoritism (Gautam et al., 2014). Moderately high mean scores for "lack of proper time management" (73.50, Rank VI) and "lack

Table 1. Garrett ranking of constraints faced by respondents in availing cooperative society services

Constraints faced by the respondents	Mean Garrett Score	Total Garrett Score	Rank
Financial and credit Constraints			
Inadequate capital accumulation	58.67	7040.40	XII
High rate of interest	56.83	6819.60	XIII
Slow recovery of the loan	83.33	9999.60	II
Long time for approval of credit	60.50	7260.00	XI
Administrative and Governance Constraints			
Misused by cooperative staff	63.17	7580.40	X
Government interference	47.17	5660.40	XVII
Lack of cooperation by society staff	53.67	6440.40	XIV
Lack of management by the elected board	71.50	8580.00	VII
Lack of proper time management	73.50	8820.00	VI
Institutional and Procedural Constraints			
Unavailability of the law	81.50	9780.00	III
Procedures and policies are difficult for common people to understand	75.17	9020.40	V
Operational and Supply Chain Constraints			
Inputs are not available at the right time	87.76	10531.20	I
Lack of quality seeds	65.83	7899.60	IX
Lack of quality fertilizers	79.83	9579.60	IV
Technical problems	42.67	5120.40	XIX
Labour shortage	45.50	5460.00	XVIII
Educational and Socio-Psychological Factors			
Illiteracy among farmers	69.67	8360.40	VIII
Lack of awareness among the members of society	51.67	6200.40	XV
Lack of skilled personnel	35.83	4299.60	XX
Informational and Market Constraints			
Weak market information	49.83	5979.60	XVI

of management by elected board" (71.50, Rank VII) indicate disagreement with internal management procedures. Decisions may be postponed, meetings may not take place on schedule, and the elected board may not be able to adequately supervise daily operations (Kumar et al., 2020; Pathania & Meena, 2025). Middle-ranked constraints, such as illiteracy among farmers, lack of quality seeds, and misuse by cooperative staff, show that while there are concerns about human resources, they are not as urgent as issues related to immediate service and legal matters (Gautam et al., 2014; Krishna et al., 2024). Conversely, lack of skilled personnel, technical problems, labor shortages, and government interference received lower mean Garrett scores, placing them at the bottom of the ranking list (XVII to XX). This does not mean they are entirely unimportant; rather, members currently see them as less urgent than issues such as timeliness, quality, and clarity of the law (Kumar et al., 2020; Sabu and Roy, 2024). Overall, the ranking pattern clearly indicates that, for these farmers, the core pain points are the timeliness and quality of services and the clarity of rules, rather than a physical shortage of labor or equipment. Other Garrett ranking tests conducted in other regions of India have shown a very similar dominance of constraints related to government and service quality (Das et al., 2014; Verma & Kumawat, 2020: Ao & Jamir, 2020).

CONCLUSION

The study revealed that members of primary agricultural cooperative societies face several constraints in accessing cooperative services. The Garrett ranking analysis showed that the major constraints experienced by farmers were the non-availability of inputs at the right time, slow loan recovery, unclear regulations, lack of quality fertilizers, and complex procedures. In contrast, issues such as a lack of skilled personnel and minor technical problems were perceived as less severe. Farmers suggested improvements, including timely delivery of inputs, better technical and marketing support, availability of quality seeds and fertilizers, and provision of affordable credit. Addressing these issues can enhance the efficiency of cooperative societies and improve farmers' access to institutional agricultural services.

DECLARATIONS

Ethical Approval and Consent to Participate: The present study did not require formal ethical approval in accordance with institutional and national guidelines. However, informed consent was obtained from all respondents prior to data collection.

Consent for Publication: All participants provided their consent for the publication of the data included in this study.

Availability of Data and Materials: The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Competing Interests: The authors declare that they have no competing interests.

Author Contributions: AG and RKD conceptualized the research. AG, RKD, and AV developed the experimental design, while AG,

RKD, and SS contributed experimental materials. AG conducted a field survey and data collection. SS and AV performed data analysis and interpretation, and the manuscript was prepared and drafted by MRA. All authors reviewed and approved the final manuscript.

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Research Note

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Analysis and Prioritization of Constraints Affecting ICT Tools Adoption among KVK Personnel

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HIGHLIGHTS

- Insufficient training was the most severe constraint affecting ICT adoption among KVK personnel.
- Technical, economic, and infrastructural issues significantly influenced ICT utilization in extension services.
- Capacity building and technical support are essential for improving ICT adoption efficiency.

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Keywords: KVK personnel, Constraints, Garrett ranking technique, ICT adoption, Agricultural extension services, Capacity-building.

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ABSTRACT

Information and communication technology (ICT) emerged as a crucial instrument for enhancing the dissemination of information and bolstering agricultural extension services. The current study was conducted in 2025–2026 with the aim of identifying and ranking the constraints to the adoption of ICT technologies that Krishi Vigyan Kendra (KVK) staff at Acharya Narendra Deva University of Agriculture and Technology, Uttar Pradesh, faced. Using a multi-stage sample process and an ex post facto study approach, 142 KVK employees were chosen. A structured interview schedule was used to gather data, and the Garrett ranking method was used for analysis. The results showed that the lack of training opportunities was the biggest constraint, followed by psychological constraints and a lack of technical know-how. Other significant constraints included frequent technical changes, expensive maintenance costs for ICT tools, and software-related problems. However, limitations pertaining to data privacy, interoperability, and intellectual property rights were seen as less serious. The study emphasized the necessity of better infrastructure, increased technical assistance, and capacity-building programs to guarantee extension staff members' efficient use of ICT tools.

INTRODUCTION

Agricultural extension is undergoing a significant transformation with the integration of Information and Communication Technology (ICT). ICT has emerged as a powerful tool for enhancing information dissemination and strengthening decision-making among stakeholders. It facilitates effective communication through digital platforms such as mobile phones, internet services, and software applications, thereby bridging the gap between research and farmers (Mukherjee & Jha, 2024). As a result, extension services have become more responsive, demand-driven, and accessible, contributing to improved agricultural productivity and rural livelihoods. ICT's involvement in agricultural growth has grown significantly in recent years because of its capacity to give farmers fast, location-specific information. By facilitating knowledge exchange between researchers, extension staff, and farming communities, ICT tools improve the overall effectiveness of extension services (Satapathy et al., 2024a). The need for training of extension officers in the deficient areas was well highlighted by

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Paul et al. (2015). Furthermore, ICT has made it possible to provide real-time communication, online training courses, and digital advisory services all of which are crucial to contemporary agriculture. Despite its promise, several barriers affect how ICT technologies are adopted and used in agriculture. ICT adoption is greatly impacted by technical, economic, and social variables, such as ignorance, poor infrastructure, and restricted access to support services, according to studies (Satapathy et al., 2024b). In the same way, the degree to which extension workers use ICT is greatly influenced by elements including training, organizational culture, and the accessibility of ICT services (Shashidhara, 2020). Furthermore, the efficient use of ICT tools is still hampered by a lack of experience and insufficient abilities. Krishi Vigyan Kendras (KVKs) are the front-line extension system in India that disseminates agricultural innovations and develops farmer capacity. The role of scientific staff in KVK is very crucial, vital and multifarious to address and support farmers in their decision process enabling them to achieve their goals of higher farm income (Sinha et al., 2021). The proficiency and technological preparedness of extension staff play a major role in the efficient operation of KVKs. However, the effective use of ICT tools in extension efforts is limited by a number of factors, including lack of training, technical challenges, infrastructure limits, and workload issues. Furthermore, research has shown that ICT use in extension is still uneven, necessitating systematic measures to improve its efficacy (Haqyar et al., 2025). While several studies have looked at ICT accessibility and usage. However, limited studies have systematically identified and prioritized the constraints faced specifically by KVK personnel. Most existing studies report constraints without ranking their severity. Therefore, this study aims to fill this gap by identifying and prioritizing constraints affecting ICT tools adoption among KVK personnel.

METHODOLOGY

The study was conducted using an ex-post facto research design, as the variables under investigation had already occurred and were beyond the control of the researcher (Kerlinger, 1964). The study was carried out among Krishi Vigyan Kendra (KVK) personnel working under the jurisdiction of Acharya Narendra Deva University of Agriculture and Technology, Ayodhya, Uttar Pradesh. A multi-stage sampling technique was followed for the selection of respondents (Cochran, 1977). In the first stage, KVKs under ANDUAT were selected purposively based on their active involvement in extension activities and ICT-based advisory services, ensuring that respondents had relevant experience with ICT tools. In the second stage, KVK personnel including Subject Matter Specialists, Programme Assistants, and other extension staff were selected, as they were directly involved in the use of ICT tools for agricultural communication. A total of 142 respondents were included in the study, ensuring representation of different categories of extension personnel. The sample size was determined using the formula suggested by Cochran (1977): $n = (Z^2 \times p \times q) / e^2$, where: n = sample size, Z = 1.96 (95% confidence level), p = 0.5, q = 1 – p, e = 0.05, Based on this, the sample size was calculated and 142 respondents were selected. Data were collected through personal interviews using a well-structured and pre-tested interview schedule, ensuring that respondents had relevant experience with ICT tools. The schedule included various constraints related to the adoption and utilization of ICT tools. The constraints were identified through review of literature, expert consultation, and discussion with KVK personnel. A total of 15 constraints were considered, covering infrastructural, technical, economic, institutional, and personal aspects. The constraints were examined and ranked using the Garrett ranking method (Garrett and Woodworth, 1969). The discovered restrictions were ranked by the respondents according to their severity. The following formula was used to convert the ranks into percent position: Percent Position = $100 (Rb_{ij} – 0.5) / N_j$, where N_j represented the total number of constraints ranked and R_{ij} represented the rank given for the ith constraint by the jth respondent. The Garrett conversion table was used to translate the % positions into Garrett scores. Each constraint's mean score was determined and arranged in descending order. Further, suggestions provided by the respondents to overcome the constraints were compiled and analyzed using frequency and percentage, and ranked accordingly. These statistical tools were used to summarize and interpret the data in a simple and meaningful manner, facilitating clear understanding of the major constraints and suggested measures.

RESULTS

The Garrett ranking technique was used to identify and prioritize the constraints affecting ICT adoption among KVK personnel (Table 1). The results indicate that insufficient training opportunities was the most severe constraint, highlighting the critical need for capacity-building initiatives. This was followed by physiological constraints and limited technical knowledge, suggesting that both human and skill-related factors significantly influence ICT utilization. Among technical constraints, software and virus-related problems and high repair costs of ICT tools were found to be major barriers. In addition, frequent technological updates also posed challenges, indicating difficulties in adapting to rapidly changing digital tools. Moderate constraints included high cost of devices and services**,** poor infrastructure and connectivity, and limited competence in handling ICT tools. In contrast, institutional and policy-related constraints, such as lack of resources, administrative workload, data privacy concerns, interoperability issues, and intellectual property concerns, were perceived as less severe. Overall, the findings reveal that training, technical, and individual-level constraints are more critical compared to institutional and policy-related issues in influencing ICT adoption among KVK personnel.

DISCUSSION

The results of the Garrett Ranking technique provide important insights into the constraints affecting ICT adoption among KVK personnel. The findings clearly indicate that lack of training is the most critical barrier, reflecting inadequate exposure and limited opportunities for ICT-oriented capacity building among extension staff. As reported by Kale et al. (2017), lack of training facilities is a major constraint among KVK scientists, while Agwu and Ogbonnah (2014) also emphasized that inadequate training and technical expertise significantly hinder ICT utilization. Similarly,

Table 1. Garrett Ranking of Constraints in the Adoption of ICT Tools among KVK Personnel

S.No.	Statements	Percent Position	Garrett Value	Garret Score	Rank
1	Inadequate infrastructure and poor connectivity limit effective use.	56.67	47	21.51	IX
2	Insufficient training opportunities restrict skill development.	03.33	85	75.42	I
3	Limited technical knowledge reduces confidence in use.	16.67	69	50.53	III
4	The high cost of devices and services discourages adoption.	50.00	50	25.35	VIII
5	Physiological Constraints	10.00	75	61.79	II
6	Lack of institutional and financial resources.	70.00	40	15.49	XI
7	Problem of software and viruses.	23.33	65	44.40	IV
8.	Competence in handling ICT tools.	63.33	43	17.86	X
9.	Excessive usage of ICT tools has affected socialising with family and friends.	43.33	53	30.97	VII
10.	High cost of repairing ICT tools.	30.00	60	38.45	V
11.	Concerns regarding data privacy and security discourage users from adopting ICT tools.	83.33	31	08.95	XIII
12.	Frequent technological updates and rapidly changing digital platforms create difficulties in continuous adoption.	36.67	57	35.72	VI
13.	Heavy administrative workload reduce he time available for effectively utilising ICT tools in research and extension activities.	76.67	36	11.40	XII
14.	Lack of interoperability between different ICT systems and database limits efficient information exchange.	90.00	25	06.16	XIV
15.	Concerns about intellectual property rights while sharing digital research outputs discourage ICT based collaboration.	96.67	15	02.95	XV

Meera et al. (2004) highlighted that skill development plays a crucial role in successful ICT integration. These findings suggest that training remains a fundamental requirement for enhancing digital competencies in extension systems. The prominence of physiological constraints further indicates that prolonged use of ICT tools may lead to discomfort, fatigue, and reduced productivity. Although limited research is available in agricultural extension, similar patterns have been observed in broader digital work environments. In addition, the constraint related to limited technical knowledge emphasizes the importance of digital literacy in ensuring effective adoption. Hashemi et al. (2014) found that technical proficiency significantly influences ICT usage, while Mittal and Mehar (2016) and Panda et al., (2019) reported that lack of digital skills remains a major barrier among agricultural stakeholders. These findings indicate that ICT adoption is not merely a technical issue but also a human-centric challenge involving behavioral and capacity-related dimensions. Technical constraints such as software issues, virus risks, poor connectivity, and frequent technological updates were also identified as significant barriers. Klerkx et al. (2019) emphasized that digital agriculture requires continuous learning due to rapidly evolving technologies, which supports the present findings. Similarly, Arokoyo (2005) reported that inadequate infrastructure and poor connectivity are major obstacles to ICT use in extension services. These results highlight the dynamic and complex nature of ICT tools and the need for continuous adaptation. Financial and infrastructural limitations, including the high cost of ICT tools, maintenance expenses, and inadequate connectivity, were also found to hinder adoption. Aker (2011) observed that financial and infrastructural barriers significantly influence ICT usage in developing countries. Likewise, Frempong et al. (2006) and Singh et al. (2015) reported that high costs and inadequate infrastructure restrict the effective use of ICT tools in agricultural extension. These findings indicate that economic constraints continue to limit ICT accessibility and utilization. Furthermore, institutional constraints such as heavy administrative workload and lack of organizational support were found to reduce the effective utilization of ICT tools. Kumar et al. (2018) highlighted those institutional barriers, including workload and lack of support, hinder ICT adoption among extension personnel. Davis and Franzel (2018) also emphasized the importance of supportive work environments for effective extension services. In addition, psychological and social constraints, such as reduced social interaction and health concerns due to excessive ICT use, indicate emerging challenges associated with digital work environments, as also noted by Sharma (2018). Overall, the study indicates that ICT adoption among KVK personnel is influenced by a combination of training, technical, financial, infrastructural, and institutional factors. The findings emphasize the need for a comprehensive and integrated approach that focuses on capacity building, continuous technical support, infrastructure development, and strengthening institutional mechanisms. Such an approach is essential to enhance the effectiveness of ICT-enabled agricultural extension services. The consistency of these findings with previous research further strengthens the validity of the study.

CONCLUSION

The research investigation found that a number of problems, mostly related to training, technical expertise, and physiological constraints, hindered KVK employees' adoption and efficient use of ICT technologies. The most important limitation was found to be a lack of training opportunities, highlighting the necessity of ongoing capacity-building initiatives. ICT use was further limited by a lack of technical expertise and problems with software, upkeep, and rapid technological modifications. Adoption was also somewhat impacted by infrastructure limits and financial restrictions such the expensive cost of devices and repairs. Constraints relating to institutions and policies, however, were seen as less serious. The

results indicate that ICT adoption can be greatly increased by bolstering training initiatives, upgrading technical support systems, and boosting infrastructure. A coordinated and systematic approach is essential to enhance the efficiency of ICT-enabled agricultural extension services among KVK personnel.

DECLARATIONS

Ethical approval and consent to participate: Informed consent was obtained from all respondents prior to data collection.

Consent for publication: All participants provided their consent for the publication of the data included in this study.

Competing interests: The authors declare that they have no competing interests.

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Research Note

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Exploring Entrepreneurial Behaviour among Rural Women in Dairy Cooperatives

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HIGHLIGHTS

- Beneficiaries exhibited higher entrepreneurial traits than non-beneficiaries.
- Participation in dairy cooperatives improved decision-making and leadership abilities.
- Mass media exposure supported entrepreneurial development among beneficiaries.
- Economic benefit and family support influenced participation in the dairy enterprise

ARTICLE INFO

Keywords: Women dairy cooperatives, Entrepreneurial traits, Beneficiaries, Rural women, Extension education.

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ABSTRACT

The study was conducted in 2025 in the Begusarai and Samastipur districts of Bihar to examine the socio-economic profile and entrepreneurial traits of beneficiaries and non-beneficiaries of women's dairy cooperatives. A descriptive research design was adopted, and a total of 260 respondents, comprising 200 beneficiaries and 60 non-beneficiaries, were selected through a multistage sampling procedure. Data were collected using a structured interview schedule and analysed using frequency, percentage and the chi-square test. The findings revealed that beneficiaries were relatively better placed in terms of socio-economic characteristics and exhibited higher levels of social participation and access to information sources. A majority of beneficiaries (70.50%) were found to possess medium entrepreneurial traits, followed by high level (20.50%), whereas most non-beneficiaries (61.67%) fell under the low category. The chi-square analysis indicated a significant association between beneficiary status and entrepreneurial traits. The study concludes that participation in women's dairy cooperatives plays a crucial role in enhancing entrepreneurial behaviour, access to information and overall socio-economic development of rural women. Strengthening extension services and promoting wider participation in cooperative activities can further improve entrepreneurial capabilities and livelihood opportunities.

INTRODUCTION

In many rural areas, women involved in cooperative activities have gradually taken on responsibilities such as milk marketing, financial management, and participation in group decision-making. These experiences contribute to the development of confidence, leadership ability, and economic independence, thereby reinforcing the role of cooperative institutions in promoting entrepreneurial behaviour among rural women. Women associated with such collective systems often benefit from training programmes, extension support and improved access to information, which together foster entrepreneurial growth. In contrast, those outside organised structures frequently encounter constraints such as limited awareness, reduced institutional access and lower participation in developmental activities.

Entrepreneurial traits play a crucial role in efficiently managing dairy enterprises and improving productivity and income for rural women. Women who are associated with cooperative institutions are more likely to gain exposure to training programmes, extension services, and information sources, which contribute to the

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development of these traits. On the other hand, women who are not part of such organisations often face constraints related to limited awareness, limited access to resources, and lower levels of social participation.

Previous studies have highlighted the important role of cooperative institutions and extension interventions in promoting entrepreneurial development among rural women. Participation in dairy cooperatives has been found to enhance income, decision-making ability, and access to resources, thereby contributing to women's empowerment. Women engaged in such institutional frameworks tend to develop better managerial skills and confidence due to regular interaction, training exposure, and collective functioning.

Entrepreneurial behaviour among rural women is influenced by factors such as education, access to information, and social participation (Gupta et al., 2013; Sharma & Singh, 2019; Kumar & Singh, 2023). Women with greater exposure to extension services and communication channels are more likely to adopt improved practices and demonstrate higher levels of initiative and innovation. Women with greater exposure to extension services and communication channels are more likely to adopt improved practices and demonstrate higher levels of initiative and innovation. However, women who are not associated with organised groups often face limitations in terms of access to information and institutional support, which affects their entrepreneurial development.

Studies reported in the *Indian Journal of Extension Education* have further emphasised that participation in dairy-based enterprises and extension programmes significantly improves economic motivation, leadership ability, and social participation among rural women (Singh & Verma, 2022; Kumar et al., 2023; Yadav & Patel, 2024). These findings highlight the importance of strengthening cooperative structures and extension efforts to enhance entrepreneurial traits and livelihood opportunities. Several studies have also reported that cooperative participation and extension support play a significant role in strengthening entrepreneurial competencies among rural women (Modak et al., 2018; Kobba et al., 2020; Bastida et al., 2022; Farnworth et al., 2023; Sharma & Singh, 2019). These studies highlight the importance of institutional support, access to information, and training in enhancing women's economic participation and entrepreneurial behaviour. Entrepreneurial behaviour among rural women has also been examined in terms of individual competencies and motivational aspects, highlighting the importance of behavioural components in enterprise development (Mubeena, 2017; Johar & Singh, 2022).

METHODOLOGY

The present investigation was conducted in 2025 in selected districts of Bihar to analyse the socio-economic characteristics and entrepreneurial traits of women associated and not associated with dairy cooperatives. A descriptive research framework was employed to examine existing conditions without the manipulation of variables. Primary data were collected using a structured interview schedule designed to capture relevant socio-economic and behavioural aspects. A multistage sampling procedure was followed for the selection of respondents. Initially, two milk unions, namely Barauni and Mithila, were purposively selected based on the active functioning of women dairy cooperative societies. From each selected milk union, one district was identified, resulting in the selection of Begusarai and Samastipur districts. Further, four villages from each district were selected, making a total of eight villages for the study.

A comprehensive list of women respondents was prepared with the help of local cooperative records and field verification. From this list, a total sample of 260 respondents were drawn, consisting of 200 beneficiaries (members of dairy cooperatives) and 60 non-beneficiaries (non-members). The respondents were selected using proportionate random sampling to ensure representation from all selected villages. Data were collected through a structured interview schedule designed to capture information on socio-economic characteristics, mass media exposure and entrepreneurial traits. Entrepreneurial traits were assessed using selected indicators such as decision-making ability, leadership, risk-taking behaviour and innovativeness. Based on the obtained scores, respondents were categorised into low, medium and high levels using appropriate statistical measures. The collected data were systematically coded, classified, and analysed using appropriate statistical techniques. Descriptive measures such as frequency and percentage were applied for summarisation, while the chi-square test was used to examine the relationship between beneficiary status and entrepreneurial traits.

RESULTS

The findings of the study are presented to describe the socio-economic characteristics, mass media exposure and entrepreneurial traits of beneficiaries and non-beneficiaries of women's dairy cooperatives.

Entrepreneurial traits

The distribution of respondents according to entrepreneurial traits is presented in Table 1.

Table 1. Distribution of respondents based on entrepreneurial traits

Category	Beneficiaries (%)	Non-beneficiaries (%)
Low	9.00	61.67
Medium	70.50	38.33
High	20.50	0.00
Total	100.00	100.00

The findings show a clear difference in entrepreneurial traits between beneficiaries and non-beneficiaries of dairy cooperatives. A larger proportion of beneficiaries were concentrated in the medium and high categories, while non-beneficiaries were predominantly found in the low category. This pattern suggests that participation in cooperative institutions contributes to the gradual development of entrepreneurial competencies among rural women. Such differences can be explained by the greater exposure of beneficiaries to training, extension services, and group-based activities, which support skill development and confidence building. Similar trends have been reported in earlier studies, where cooperative

participation was found to enhance decision-making ability, economic motivation, and social participation among women (Kobba et al., 2020; Kumar & Singh, 2023; Yadav & Patel, 2024). Likewise, Singh and Verma (2022) observed that access to extension education and information sources plays an important role in improving behavioural outcomes and entrepreneurial capacity among rural populations.

Reasons for choosing a dairy enterprise

The reasons for choosing the dairy enterprise among beneficiaries are presented in Table 2.

Table 2. Reasons for choosing dairy enterprise by beneficiaries

Reasons	Percentage	Rank
Economical enterprise	87.50	I
Family support	81.50	II
Social recognition	76.00	III
Veterinary facilities	75.00	IV
Government schemes	73.50	V
Family influence	72.50	VI
Society influence	70.50	VII
Own interest	62.50	VIII
Neighbour influence	37.50	IX

The findings suggest that economic benefit was the most important factor influencing women to engage in dairy enterprises. In addition, family support and the desire for social recognition also played a significant role in motivating participation. This indicates that both economic and socio-cultural factors jointly shape women's involvement in livelihood activities. The dominance of economic motivation reflects the need for stable and regular income among rural households, while family encouragement appears to facilitate women's active participation in such enterprises. Similar observations have been reported in earlier studies, where economic gain and household support were identified as key drivers of women's engagement in dairy-based activities (Yadav & Patel, 2024; Kumar & Singh, 2023). Furthermore, research has shown that social recognition and community acceptance can enhance women's confidence and willingness to participate in entrepreneurial activities (Sharma & Singh, 2019).

Association between beneficiary status and entrepreneurial traits

The association between beneficiary status and entrepreneurial traits is presented in Table 3.

Table 3. Association between beneficiary status and entrepreneurial traits

Category	Beneficiaries	Non-beneficiaries	Total
Low	18	37	55
Medium	141	23	164
High	41	0	41
Total	200	60	260

$\chi^2 = 82.63$, df = 2, $p < 0.01$

The chi-square analysis showed a statistically significant association between beneficiary status and entrepreneurial traits, indicating that women who are members of dairy cooperatives tend to exhibit stronger entrepreneurial behaviour than non-members. This relationship suggests that participation in cooperative institutions provides a supportive environment for the development of skills such as decision-making, leadership, and initiative.

The observed association can be linked to the regular exposure of beneficiaries to training programmes, extension services, and group interactions, which collectively enhance their capacity to manage enterprise-related activities. Similar findings have been reported in earlier studies, where cooperative participation was found to positively influence entrepreneurial orientation and economic behaviour among rural women (Kumar & Singh, 2023; Yadav & Patel, 2024). In addition, Singh and Verma (2022) highlighted that access to extension education and institutional support plays a significant role in bringing about behavioural change and improving entrepreneurial competencies.

DISCUSSION

The findings of the present study underline the significant role of dairy cooperatives in shaping the entrepreneurial behaviour of rural women. Women associated with cooperative institutions exhibited relatively stronger entrepreneurial traits, better access to information, and improved socio-economic positioning compared to non-members. This indicates that cooperative participation goes beyond economic support and contributes to behavioural transformation. Improved access to communication channels and extension services appears to be a key factor behind this difference. Women who are regularly exposed to training, advisory services, and group interactions are better equipped to make informed decisions and adopt improved dairy practices. Such exposure enhances confidence, encourages initiative, and promotes active engagement in income-generating activities. The results suggest that information access functions as a catalyst in developing entrepreneurial orientation among rural women.

The statistically significant association observed in the study further confirms that institutional linkage plays a decisive role in influencing entrepreneurial behaviour. Cooperative platforms provide an enabling environment where women can learn collectively, share experiences, and gradually build managerial and decision-making skills. In contrast, women outside these systems often remain constrained by limited information flow and a lack of institutional guidance. These observations are consistent with earlier studies. Kumar and Singh (2023) reported that engagement in dairy enterprises strengthens economic motivation and decision-making ability among rural women. Similarly, Yadav and Patel (2024) found that cooperative participation enhances income opportunities and social involvement. Singh and Verma (2022) also highlighted that extension-oriented educational efforts contribute to behavioural change and skill development. The present study supports these findings by demonstrating that both cooperative participation and access to information significantly influence entrepreneurial characteristics.

However, the continued presence of non-beneficiaries with lower entrepreneurial scores indicates gaps in outreach and inclusion.

Limited access to institutional support and information sources restricts their ability to develop similar competencies. This points to the need for expanding extension efforts and ensuring wider participation of rural women in cooperative frameworks. From a practical perspective, strengthening training programmes, improving access to mass media, and promoting inclusive cooperative membership can substantially enhance entrepreneurial development. Such efforts can contribute not only to improved livelihoods but also to greater empowerment and self-reliance among rural women.

CONCLUSION

The study demonstrates that participation in women's dairy cooperatives significantly enhances entrepreneurial behaviour and socio-economic conditions among rural women. Members show better access to information, stronger decision-making ability, and greater confidence compared to non-members, indicating the positive role of cooperative platforms in behavioural development. The gap observed between beneficiaries and non-beneficiaries highlights the need to expand the reach of such institutions. Strengthening extension support, improving access to training, and promoting wider inclusion can help bridge this gap. Overall, dairy cooperatives provide an effective mechanism for fostering entrepreneurship and improving livelihoods. Focused efforts to enhance their accessibility and functioning can contribute meaningfully to rural women's empowerment and sustainable development.

DECLARATIONS

Ethical approval and consent to participate: Informed consent was obtained from all respondents prior to data collection.

Consent for publication: All participants provided their consent for the publication of the data included in this study.

Competing interests: The authors declare that they have no competing interests.

Conflict of interest: The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have critically reviewed, revised, and approved the manuscript and take full responsibility for its content.

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Assessment of Farmers' Adoption of Improved Groundnut Cultivation Practices in Bundelkhand Region of Uttar Pradesh

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HIGHLIGHTS

- Time and method of sowing recorded the highest adoption index (72.84) among all production technology components.
- Crop diversification was the least adopted practice (49.83), indicating a critical gap in sustainable intensification strategies.
- Information source exerted the highest total effect (0.5822) on adoption, underscoring the centrality of extension access.

ARTICLE INFO

Keywords: Technology adoption, Groundnut, Bundelkhand, Path analysis, Sustainable production.

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ABSTRACT

The study was conducted during 2025–2026 in the semi-arid Bundelkhand region of Uttar Pradesh, India, to examine the socioeconomic, institutional, and behavioral determinants of groundnut production technology adoption and to map pathways linking adoption to sustainable production outcomes. A multi-stage stratified random sampling design was employed to select 480 groundnut-growing households from 32 villages across Jhansi and Mahoba districts. Primary data were collected through a pre-tested structured interview schedule administered via face-to-face personal interviews. Adoption was assessed across 11 technology components covering 61 discrete practices using a three-point scale and summarized as an Adoption Index. Results indicated that time and method of sowing recorded the highest Adoption Index (72.84), while crop diversification was the least adopted (Adoption Index: 49.83). A majority (75.63%) of farmers fell in the medium adoption category. Pearson correlation analysis revealed that family size (r = 0.459), information source (r = 0.582), and knowledge level (r = 0.448) were significantly associated with adoption. Path coefficient analysis identified information source and family size as variables with the highest total effects on adoption. These findings highlighted the need for context-specific extension strategies to bridge adoption gaps in resource-constrained semi-arid farming systems.

INTRODUCTION

Groundnut (*Arachis hypogaea* L.) is a crop of foundational importance to India's food and oilseed economy. In India, groundnut is cultivated across 5.76 million hectares with a total production of 11.94 million tonnes and a yield of 2,073 kg ha^{-1} during 2024–25, accounting for 35.3% of total oilseeds produced (Department of Agriculture and Farmers Welfare [DAFW], 2025). Despite occupying the largest area under groundnut cultivation globally, India's productivity lags significantly behind China and the United States. The primary factors contributing to low productivity include the crop's confinement to rainfed areas (approximately 85%), high susceptibility to weather variability, and soils of low fertility and light texture, compounded by non-availability of quality seed at the right time, uneven fertiliser use, and deficient crop management (Meena et al., 2025).

These structural constraints are further amplified by accelerating climate instability. Groundnut is grown in marginal arid

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and semi-arid agro-ecosystems with wide yield fluctuations due to spatial variability of rainfall and soil. Climate change is predicted to increase intra- and inter-annual rainfall variability, further constraining the groundnut economy beyond existing economic and social pressures (Chilwal et al., 2025). The semi-arid Bundelkhand region of central India, spanning thirteen districts across Uttar Pradesh and Madhya Pradesh, exemplifies this convergence of agronomic vulnerability and structural underinvestment.

The prolonged dominance of single-crop-based groundnut systems, unbalanced fertiliser use, and reduced application of organic manure have acutely aggravated production vulnerabilities in the region, threatening both household food security and long-term soil health (Bana et al., 2024). Tripathi et al. (2023) observed declining trends in productivity of oilseed crops across the Bundelkhand region of Uttar Pradesh, reinforcing the urgency for technology-led intensification.

Technology adoption among smallholders in dryland India is, however, neither automatic nor assured. The determinants of adoption differ based on household attributes, the specific technology, and geographical location. One key finding across the literature is the existence of substantial diversity in adoption factors, suggesting that context-specific analysis is essential for accurate policy design (Kumar & Nain, 2012; Ruzzante et al., 2021). In Bundelkhand evidence confirms that socioeconomic and behavioral factors are equally important as agronomic ones. Jatav (2024) demonstrated that entrepreneurial orientation, risk-taking, innovativeness, and pro-activeness, were significant factors influencing farmers' adoption of climate-smart agriculture practices, while education was linked to acceptance of certified seed and soil testing technologies. Jha et al. (2024) similarly underscored that institutional access and information exposure critically shape the multi-technology adoption decisions of smallholder farmers. Despite the region's strategic importance as a groundnut-producing zone and the mounting evidence that technology adoption can raise system productivity by up to 24% (Choudhary et al., 2022), a comprehensive understanding of the determinants of technology adoption and their linkage to sustainable production pathways in semi-arid Bundelkhand remains absent from the literature.

METHODOLOGY

The present study was conducted during 2025–26 in the Bundelkhand region of Uttar Pradesh, India, a semi-arid agro-ecological zone characterised by recurrent drought episodes, high inter-annual rainfall variability, and structurally fragile smallholder farming systems. Two districts, Jhansi and Mahoba, were purposively selected based on two criteria: the significant proportion of gross cropped area under groundnut cultivation, and the documented vulnerability of these districts to climatic stress and resource constraints that suppress productivity below regional potential. Both districts are representative of the broader agrarian challenges confronting groundnut farmers across the Bundelkhand landscape. A multi-stage stratified random sampling design was employed to ensure spatial representativeness and minimize selection bias. In the first stage, four blocks per district were selected purposively, based on the extent of area under groundnut cultivation, yielding eight blocks in total. In the second stage, four villages were selected from each block through simple random sampling, producing 32 villages across both districts. In the third stage, from the complete household listing in each selected village, 15 groundnut farmers were randomly selected, yielding a final analytical sample of 480 groundnut-growing households. Primary data were collected through a structured and pre-tested interview schedule administered via face-to-face personal interviews, supplemented by direct field observation. The schedule comprised multiple thematic sections covering socio-economic characteristics, institutional access (credit, extension contact, and market linkage), psychological attributes (risk orientation, innovativeness, and scientific orientation), and adoption of eleven components of improved groundnut production technology spanning 61 discrete practices, including improved seed varieties, seed treatment, nutrient management, and integrated plant protection measures.

Adoption level was assessed on a three-point scale: fully adopted (3), partially adopted (2), and not adopted (1), with a maximum attainable adoption score of 183 (61 practices × 3). An Adoption Index was computed as the ratio of the respondent's actual adoption score to the maximum possible adoption score, multiplied by 100. The relationship between socio-economic independent variables and adoption scores was examined using Pearson product-moment correlation analysis. To identify variables exerting the strongest net influence on adoption and to quantify the direct and indirect channelling effects of predictor variables, path coefficient analysis was performed following the procedure outlined by Dewey and Lu (1959). All statistical tests were interpreted at the 5% level of significance, and data were processed using SPSS version 25.0 and R studio.

RESULTS

Adoption index across technology components

Table 1 presents the adoption index across eleven components of improved groundnut production technology. Among all components, time and method of sowing recorded the highest adoption index (72.84), ranked first, followed by irrigation management (71.08, rank II) and field preparation (70.67, rank III). Recommended varieties and sowing practices ranked fourth (69.98), while intercultural operations (66.79) and marketing practices (65.85) ranked fifth and sixth, respectively. Manure and fertiliser

Table 1. Adoption index across groundnut production technology components

S.No.	Technology Component	Adoption Index	Rank
1	Field preparation	70.67	III
2	Recommended varieties and sowing	69.98	IV
3	Time and method of sowing	72.84	I
4	Manure and fertilisers	65.84	VII
5	Irrigation management	71.08	II
6	Intercultural operation	66.79	V
7	Crop diversification	49.83	XI
8	Insect and pest management	64.15	IX
9	Disease management	59.44	X
10	Harvesting	65.21	VIII
11	Marketing	65.85	VI

application (65.84) and harvesting practices (65.21) ranked seventh and eighth. Insect and pest management (64.15) and disease management (59.44) occupied the ninth and tenth ranks. Crop diversification recorded the lowest adoption index (49.83) and was ranked last (XI), indicating it as the most critical gap in the adoption of sustainable groundnut intensification practices.

Correlation between independent variables and adoption

The Pearson correlation coefficients between independent variables and adoption score are presented in Table 2. Among the socioeconomic variables, family size ($r = 0.459$, $p < 0.001$), land holding ($r = 0.432$, $p < 0.001$), and annual income ($r = 0.412$, $p < 0.001$) were positively and significantly correlated with adoption. Age showed a significant negative correlation ($r = –0.138$, $p < 0.01$), indicating that younger farmers were relatively more likely to adopt improved technologies. Gender ($r = 0.092$, $p < 0.05$) and family type ($r = –0.101$, $p < 0.05$) were also significantly associated with adoption. Education, formal source, informal source, and extension content did not show statistically significant correlations with adoption. Among psychological variables, risk orientation ($r = 0.283$), economic motivation ($r = 0.261$), cosmopolitan outlook ($r = 0.258$), and scientific orientation ($r = 0.239$) all showed significant positive correlations ($p < 0.001$). Knowledge level ($r = 0.448$, $p < 0.001$) and information source ($r = 0.582$, $p < 0.001$) were the strongest correlates of adoption observed in this study.

Table 2. Correlation between independent variables and adoption score

Variable	Correlation (r)
Age	-0.1382**
Gender	0.0918*
Education	0.0083^{NS}
Family type	-0.1013*
Size of family	0.459***
Land holding	0.432***
Annual income	0.4121***
Formal source	0.0103^{NS}
Informal source	0.0743^{NS}
Extension contact	0.0443^{NS}
Scientific orientation	0.2386***
Economic motivation	0.2606***
Risk orientation	0.2831***
Cosmopolitan outlook	0.2577***
Knowledge level	0.4478***
Information source	0.5822***

NS = Not significant; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Path coefficient analysis of determinants of adoption

Table 3 presents the results of path coefficient analysis examining the direct and indirect effects of independent variables on adoption. Information source (X16) recorded the highest total indirect effect (0.4728), routed substantially through annual income (X7), family size (X5), and risk orientation (X13), while its direct path coefficient was 0.1094. Knowledge level (X15) also exhibited a high total indirect effect (0.3618), channelled through information source (X16), economic motivation (X12), and scientific orientation (X11), with a direct coefficient of 0.0859. Among variables with strong direct effects, economic motivation (X12) registered the highest direct path coefficient ($\beta = 0.2821$), followed by risk orientation (X13, $\beta = 0.2648$), size of family (X5, $\beta = 0.2509$), cosmopolitan outlook (X14, $\beta = 0.2448$), annual income (X7, $\beta = 0.2446$), land holding (X6, $\beta = 0.2419$), scientific orientation (X11, $\beta = 0.2348$), and age (X1, $\beta = –0.2981$). Variables such as education (X3), formal source (X8), and extension contact (X10) showed negligible direct effects, suggesting that their influence on adoption primarily operates through mediating socioeconomic and psychological variables.

DISCUSSION

The predominance of farmers in the medium adoption category aligns with trends reported across smallholder groundnut systems in dryland India, where structural barriers including limited access

Table 3. Path coefficient analysis of independent variables with adoption

Variables	Direct effect	Indirect effect	Substantial indirect effect through single variables		
	Path coeff (β)	Total Indirect Effect	I	II	III
Age (X1)	-0.2981	0.1599	0.0914 (X5)	0.0804 (X6)	-0.0371(X7)
Gender (X2)	0.0319	0.0599	0.0346 (X12)	0.0212 (X5)	-0.0152 (X14)
Education (X3)	-0.0235	0.0319	0.0554 (X1)	-0.0289 (X6)	-0.0281 (X5)
Family Type (X4)	-0.0104	-0.0909	-0.0419 (X5)	-0.0399 (X6)	-0.0273 (X7)
Size of Family (X5)	0.2509	0.2081	0.1726 (X6)	-0.1086 (X1)	0.0345 (X7)
Land holding (X6)	0.2419	0.1902	0.179 (X5)	-0.0991 (X1)	0.0642 (X7)
Annual income (X7)	0.2446	0.1675	0.0635 (X6)	0.0452 (X1)	0.0363 (X16)
Formal source (X8)	-0.0238	0.0341	0.037 (X16)	-0.0311 (X15)	0.0165 (X15)
Informal source (X9)	0.0194	0.0549	0.0344 (X13)	-0.0258 (X15)	0.017 (X16)
Extension content (X10)	-0.0548	0.0991	0.0536 (X9)	0.0307 (X15)	0.0207 (X13)
Scientific orientation (X11)	0.2348	0.0037	-0.0289 (X12)	-0.0282 (X1)	0.0216 (X16)
Economic motivation (X12)	0.2821	-0.0215	-0.0377 (X1)	0.0304 (X5)	-0.0241 (X11)
Risk orientation (X13)	0.2648	0.0183	0.0283 (X16)	-0.0188 (X11)	-0.0129 (X7)
Cosmopolitan Outlook (X14)	0.2448	0.0129	-0.0201 (X7)	0.0164 (X16)	-0.0119 (X6)
Knowledge Level (X15)	0.0859	0.3618	0.0587 (X16)	0.0505 (X12)	0.0479 (X11)
Information source (X16)	0.1094	0.4728	0.0811 (X7)	0.0758 (X5)	0.0685 (X13)

to inputs, credit, and reliable extension consistently suppress adoption below the high-performance threshold. The relatively higher adoption of sowing-related practices, compared to crop diversification and disease management, reflects a pattern common in semi-arid production systems where farmers prioritise technologies that offer immediate, predictable yield benefits with low perceived risk (Slathia et al., 2018).

The significant positive correlation of family size with adoption corroborates the resource endowment hypothesis: larger families provide greater labour availability and social capital, both of which facilitate information sharing and experimental practice of improved technologies (Gajbhiye et al., 2015; Jha et al., 2024, Kumar & Jha, 2025). The strong association of land holding and annual income with adoption is consistent with the broader adoption literature, where economic resources relax liquidity constraints that prevent smallholders from purchasing certified seeds, fertilisers, and pesticides required by improved technologies (Ruzzante et al., 2021; Khawale & Chinchmalatpure, 2023).

The negative association of age with adoption, and the absence of a significant association for formal education, may reflect the particular context of Bundelkhand, where informal learning through peer networks and field demonstration is often more influential than formal schooling. This finding is consistent with Jatav (2024), who reported that entrepreneurial behavioral dispositions, rather than formal education, were the primary drivers of climate-smart technology adoption in Uttar Pradesh. The strong path effects of risk orientation, economic motivation, and cosmopolitan outlook confirm that psychological readiness for innovation is a critical mediating factor between resource availability and actual adoption (Kumar & Jha, 2025).

The finding that information source exerted the highest total effect on adoption, substantially mediated through economic and structural variables, underscores the central role of extension services in unlocking the adoption potential of groundnut farmers. The indirect pathways through which information source influences adoption, via annual income, family size, and risk orientation, suggest that extension must simultaneously strengthen information delivery while addressing the socioeconomic barriers that condition its effectiveness (Kumar & Jha, 2025). Bana et al. (2024) similarly found that system-level integrated management approaches substantially improved productivity and profitability in semi-arid groundnut systems when accompanied by sustained institutional support. The low adoption of crop diversification, despite its documented role in reducing climatic vulnerability (Chilwal et al., 2025), points to the need for market-linked extension approaches that make diversification financially attractive, not just agronomically sound.

CONCLUSION

The study establishes that technology adoption among groundnut farmers in semi-arid Bundelkhand is primarily shaped by a convergence of structural resources (family size, land holding, annual income), psychological dispositions (risk orientation, economic motivation, cosmopolitan outlook), and information environment (information source, knowledge level). While most farmers have achieved medium-level adoption, substantial gaps persist in crop diversification and disease management. Information source exerts the highest total influence on adoption through multiple indirect pathways, making strengthening of extension delivery systems the single most impactful lever for accelerating adoption. Extension programmes designed for this region should integrate behavioural and motivational dimensions alongside technical content, with particular emphasis on market-linked crop diversification to advance the transition toward sustainable groundnut production in Bundelkhand. Future research may incorporate longitudinal approaches, comparative regional analyses, and advanced structural modelling techniques to better understand dynamic pathways influencing sustainable groundnut technology adoption.

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Research Note

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Understanding Farmers' Attitudes towards Natural Farming Adoption in Tarai Zone of Uttar Pradesh

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HIGHLIGHTS

- Annual income (r = 0.439) and achievement motivation (r = 0.413) were the strongest positive correlates of attitude towards natural farming adoption.
- Landholding, social participation, risk orientation, achievement motivation, and economic motivation were significant positive predictors.
- The regression model explained approximately 70 per cent of variation in farmer attitude (R^2 = 69.86%).

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ABSTRACT

Natural farming, as a chemical-free and ecologically integrated approach, is increasingly recognized as a sustainable alternative for smallholder agriculture in India. The present study was conducted during 2025–26 to assess farmers' attitudes toward natural farming and identify the socioeconomic and psychological determinants of those attitudes in the Tarai zone of Uttar Pradesh, India. An ex-post facto research design was adopted. A total of 450 respondents were selected through multi-stage stratified random sampling from four districts of the Tarai zone. Attitude was measured using a modified scale developed by Zala and Kalsariya (2022), and Pearson correlation and multiple linear regression analyses were employed to identify significant predictors. Correlation analysis revealed that landholding (r = 0.405) and annual income (r = 0.439) were significant positive correlates, while age (r = –0.331) and farming experience (r = –0.306) were significant negative correlates. Regression analysis indicated that landholding, social participation, risk orientation, achievement motivation, and economic motivation were significant positive predictors, collectively explaining 69.86 per cent of variance in attitude. The study concludes that targeted extension strategies strengthening land resource utilisation, social participation, risk-taking ability, achievement motivation, and economic motivation are essential to accelerate natural farming adoption in the region.

INTRODUCTION

Global agriculture is under mounting pressure to reconcile food production with environmental sustainability. Chemical-intensive farming systems, which dominated the post-Green Revolution era, have delivered significant productivity gains but imposed severe long-term costs on soil health, water quality, and biodiversity (Pingali, 2012; Pathak, 2023). Contemporary agricultural policy now places equal emphasis on ensuring environmental sustainability and responsibly balancing nutrient application alongside maximizing production. Against this backdrop, natural farming a chemical-free, ecologically integrated system relying on on-farm biological inputs has emerged as a credible alternative pathway for smallholder agriculture in South Asia (Bharucha et al., 2020; Kumar et al., 2025; Shanmuka et al., 2025).

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In India, natural farming has gained significant institutional momentum. The National Mission on Natural Farming (NMNF), launched in 2024, targets 7.5 lakh hectares across 15,000 clusters and aims to support one crore farmers, providing an incentive of Rs. 4,000 per acre per year for two years to encourage adoption. As of March 2025, the *Bhartiya Prakritik Krishi Paddhati* supported 28 lakh farmers practicing natural farming on 9.4 lakh hectares (GoI, 2024). Berger et al. (2025) demonstrates that Zero Budget Natural Farming delivers biodiversity and economic benefits without compromising yields, while Rasmussen et al. (2024) confirmed joint environmental and social benefits from diversified agroecological approaches.

Farmer attitude is a central psychological construct that mediates the relationship between knowledge and behavior. According to the Theory of Planned Behavior (Ajzen, 1991), attitude toward a behavior is a primary determinant of behavioral intention, which in turn drives overt action. In the agricultural context, attitude thus transforms covert behavioral intention into actual adoption decisions. Studies have shown that variables including age, family size, education, experience, landholding, extension contacts, social media use, and risk orientation significantly influence farmers' attitudes toward sustainable agricultural practice adoption (Mishra et al., 2022; Singh et al., 2024; Thangjam & Jha, 2024). In Uttar Pradesh specifically, empirical evidence confirms this attitudinal dimension: a study in Prayagraj district found that 80.00 per cent of respondents held a positive attitude toward organic farming, with inadequate marketing facilities as the dominant constraint (Mishra et al., 2022). Zero Budget Natural Farming adoption in Maharashtra identified integrated soil fertility management and integrated pest management as key adoption factors, while scarce raw materials, weed and pest management complexity, and limited knowledge of liquid fertilizers were primary constraints (Kumar et al., 2023).

The Tarai region the fertile sub-Himalayan belt of Uttar Pradesh represents a strategically significant agricultural zone where decades of chemical-intensive cultivation have compromised soil fertility and groundwater quality, yet smallholder farmers continue to rely on conventional high-input systems. The Tarai presents a distinct agro-ecological and socioeconomic context characterised by smallholder dominance, high cropping intensity, and proximity to urban markets that cannot be assumed to mirror findings from peninsular India or hill states. Region-specific evidence on farmer attitudes and their behavioral determinants toward natural farming in this zone is absent from the literature. Since attitude-behavior pathways are context-dependent, extension strategies must be calibrated to local realities (Thangjam & Jha, 2024).

METHODOLOGY

The study was conducted during 2025–26 in the Tarai agro-climatic zone of Uttar Pradesh, India, under an ex-post facto research design, which was deemed appropriate for investigating naturally prevailing conditions of farmer awareness, perception, and attitude toward natural farming without experimental manipulation of variables. The Tarai zone is characterised by rich alluvial soils, diverse cropping systems, and high dependence on agriculture for rural livelihoods. Four districts Lakhimpur Kheri, Bijnor, Bahraich, and Pilibhit were selected from the eight natural farming-practicing districts of the Tarai zone on the basis of the highest number of farmers registered under the National Mission on Natural Farming. Two districts were excluded on representativeness grounds: Shahjahanpur comprised only six per cent of its area within the Tarai zone, and Muzaffarnagar comprised only 10 per cent, making both geographically inadequate to represent Tarai-specific conditions. Seven blocks were selected from the four districts based on the highest concentration of registered natural farming practitioners. Two blocks were selected from each of the three districts with higher practitioner density Behjam and Mohammadi from Lakhimpur Kheri, Najibabad and Jalilpur from Bijnor, and Marauri and Puranpur from Pilibhit while one block, Mihinpurwa, was selected from Bahraich, which had a comparatively lower concentration of registered practitioners. From the seven selected blocks, 47 villages were selected through simple random sampling, with the number of villages allocated to each block proportional to its share of registered natural farming households, to ensure adequate spatial coverage and intra-block representativeness. A complete enumeration of registered natural farming households was conducted in each selected village, from which 10 per cent of farmers were selected proportionally by random sampling, yielding a final sample of 450 respondents. Primary data were collected through a structured and pre-tested interview schedule administered via personal interviews. Negatively worded statements in the attitude scale were reverse-scored prior to analysis. For measuring the attitude level, the modified scale developed by Zala and Kalsariya (2022) was used. Pearson product-moment correlation coefficient (r) was used to assess the direction and magnitude of association between selected independent variables and the dependent variable attitude toward natural farming. Multiple linear regression analysis was carried out to quantify the independent contribution of each socio-economic and psychological variable while holding all other predictors constant. All statistical inferences were drawn at the five per cent level of significance, and data were processed using SPSS version 25.0.

RESULTS

Statement-wise attitude of respondents towards natural farming

Table 1 presents the statement-wise distribution of respondents according to their attitude towards natural farming. Among the 19 attitude statements, the highest Weightage Mean Score (WMS) was recorded for the statement that application of crop residues and mulching improves soil aeration and water retention capacity (WMS = 4.03, Rank I), indicating near-unanimous agreement among respondents on the soil-physical benefits of natural farming practices. This was closely followed by the statement on the role of Bijamrut for seed treatment and Jivamrut as a nutrient source (WMS = 3.87, Rank II), and the belief that natural farming reduces input costs by eliminating dependence on external inputs (WMS = 3.85, Rank III). Neem leaf or neem kernel extract as an effective pest management method and natural

Table 1. Statement-wise distribution of respondents according to attitude towards natural farming

S.No.	Statements	WMS	Rank
1.	In my view, natural farming might reduce input cost because farmers do not need to take anything from outside	3.85	III
2.	I prefer natural farming because it complements other farming enterprises.	3.65	X
3.	I believe natural farming does reduce production.	3.61	XI
4.	Application of crop residues and mulching improves soil aeration and water retention capacity.	4.03	I
5.	In my opinion, irrigation requirements decrease in natural farming so water and electricity can be saved.	3.73	VII
6.	I do not believe that natural farming is the most effective solution to address global warming.	2.25	XIX
7.	I believe that farmers receive higher prices for their produce under natural farming due to access to new markets and export opportunities.	3.49	XIV
8.	Natural farming conserves beneficial soil organisms and microorganisms, thereby enhancing soil fertility.	3.73	VII
9.	I think plant grown naturally are not more tolerant to insects and disease than other farming practices	2.60	XVII
10.	I would like to advise my children to use Bijamrut for seed treatment to protect from soil-borne disease, and Jivamrut is the best source of all nutrients.	3.87	II
11.	I prefer the use of Nimastra, Brahmastra, Agniastra and Dashparni Ark for the management of sucking pests and larval infestations.	3.79	VI
12.	I think that neem leaf or neem kernel extract is an effective method for pest management.	3.83	IV
13.	Natural farming decreases the percentage of organic carbon in soil.	2.38	XVIII
14.	I believe that sustainable management and efficient utilization of natural resources can be achieved through natural farming.	3.50	XIII
15.	I am sure that natural farming reduces the incidence of non-communicable diseases.	3.19	XV
16.	I believe that one indigenous cow can support natural farming on more than five acres of land.	3.56	XII
17.	I would like that natural farming is a pain free, care free and loan free farming.	3.83	IV
18.	I think that only large landholders can successfully adopt natural farming.	2.78	XVI
19.	I don't like that natural farming increases weed infestation.	3.66	IX

WMS=Weightage Mean Score

farming as pain-free, care-free, and loan-free farming both scored equally (WMS = 3.83, Rank IV). Favourable attitudes were also recorded for the use of botanical formulations Nimastra, Brahmastra, Agniastra, and Dashparni Ark for the management of sucking pests and larval infestations (WMS = 3.79, Rank VI). A moderately positive attitude was noted toward natural farming's ability to reduce irrigation requirements and conserve water and electricity (WMS = 3.73, Rank VII), and its role in conserving beneficial soil organisms to enhance soil fertility (WMS = 3.73, Rank VII). Among the negatively worded statements, the belief that natural farming does not effectively address global warming received the lowest WMS (2.25, Rank XIX), indicating that most respondents disagreed with this view and recognised natural farming's relevance to climate mitigation. Similarly, the perception that crops under natural farming are not more resistant to insect pests and diseases (WMS = 2.60, Rank XVII) and the belief that natural farming decreases soil organic carbon percentage (WMS = 2.38, Rank XVIII) recorded low scores, reflecting that respondents largely rejected these unfavourable perceptions. The statement that only large landholders can successfully adopt natural farming returned a WMS of 2.78 (Rank XVI), suggesting that the majority did not view farm size as a binding constraint to adoption.

Correlation between independent variables and attitude towards natural farming

The correlation coefficients between selected independent variables and farmer attitude toward natural farming are presented in Table 2. Landholding (r = 0.405), annual income (r = 0.439), achievement motivation (r = 0.413), scientific orientation (r = 0.401), economic motivation (r = 0.374), social participation (r = 0.367), risk orientation (r = 0.315), occupation (r = 0.196), and environmental orientation (r = 0.135) showed significant positive correlation with attitude at the one per cent level of probability. Age (r = –0.331) and farming experience (r = –0.306) exhibited significant negative correlation at the one per cent level, while extension contact (r = –0.093) was negatively significant at the five per cent level. Education, family type, and training attended did not show statistically significant associations with attitude.

Table 2. Correlation coefficients between independent variables and attitude of farmers towards natural farming

S.No.	Variables	Correlation coefficient (r)
1.	Age	-0.331**
2.	Education	0.009 (NS)
3.	Farming Experience	-0.306**
4.	Family Type	-0.004 (NS)
5.	Landholding	0.405**
6.	Occupation	0.196**
7.	Annual Income	0.439**
8.	Social Participation	0.367**
9.	Training Attended	-0.018 (NS)
10.	Risk Orientation	0.315**
11.	Scientific Orientation	0.401**
12.	Achievement Motivation	0.413**
13.	Economic Motivation	0.374**
14.	Environmental Orientation	0.135**
15.	Extension Contact	-0.093*

* Significant at $p < 0.05$; ** Significant at $p < 0.01$; NS = Non-significant

Regression analysis of independent variables with attitude towards natural farming

The results of a multiple linear regression analysis examining the independent contribution of socioeconomic and psychological variables to farmers' attitudes are presented in Table 3. The overall model was statistically significant ($F(15, 434) = 71.02$, $p < 0.01$) with an R^2 value of 69.86 per cent, indicating that approximately 70 per cent of variation in farmer attitude was explained by the 15 independent variables collectively. Multicollinearity diagnostics indicated that variance inflation factor (VIF) values for all predictors were within acceptable limits (VIF < 5), confirming the stability of the regression estimates. Landholding ($b = 1.348$, $t = 4.251$, $p < 0.01$), social participation ($b = 0.797$, $t = 2.961$, $p < 0.01$), risk orientation ($b = 0.203$, $t = 3.102$, $p < 0.01$), achievement motivation ($b = 0.210$, $t = 2.748$, $p < 0.01$), and economic motivation ($b = 0.270$, $t = 3.606$, $p < 0.01$) emerged as significant positive predictors of attitude at the one per cent level of probability. Environmental orientation ($b = –0.249$, $t = –3.106$, $p < 0.01$) was a significant negative predictor. The negative regression coefficient for environmental orientation, despite its positive bivariate correlation with attitude ($r = 0.135$), is attributable to the suppression effects arising from its shared variance with other psychological predictors in the multivariate model; when other motivational variables are held constant, higher environmental orientation is associated with more critical evaluation of natural farming against absolute environmental benchmarks.

Table 3. Multiple linear regression analysis of factors influencing farmers' attitude toward natural farming

S.No.	Variables	Regression Coefficient (bi)	SE of bi	t-value
1.	Age	-0.116	0.094	-1.243
2.	Education	0.010	0.163	0.063
3.	Farming Experience	0.071	0.095	0.749
4.	Family Type	0.632	0.460	1.374
5.	Landholding	1.348	0.317	4.251**
6.	Occupation	0.251	0.310	0.808
7.	Annual Income	-0.404	0.268	-1.511
8.	Social Participation	0.797	0.269	2.961**
9.	Training Attended	0.141	0.237	0.596
10.	Risk Orientation	0.203	0.065	3.102**
11.	Scientific Orientation	0.111	0.084	1.314
12.	Achievement Motivation	0.210	0.076	2.748**
13.	Economic Motivation	0.270	0.075	3.606**
14.	Environmental Orientation	-0.249	0.080	-3.106**
15.	Extension Contact	0.021	0.023	0.917

* $p < 0.05$; ** $p < 0.01$

Note: The overall model was significant ($F = 71.02$, $p < 0.01$, $R^2 = 0.6986$). Variance Inflation Factor (VIF) values for all predictors were below 5.0, indicating absence of serious multicollinearity.

DISCUSSION

The favourable attitude of respondents toward natural farming across soil health, economic, and pest management dimensions is consistent with Kumari et al. (2022), who documented positive attitudinal orientation toward farm-prepared biological inputs among smallholders exposed to Zero Budget Natural Farming training. The strong endorsement of crop residue application and mulching reflects farmers' direct experience of moisture conservation benefits in semi-arid conditions. Positive attitudes toward on-farm biological inputs and botanical formulations indicate effective extension outreach (Slathia et al., 2020; Jatav, 2024). The rejection of negative perceptions regarding soil organic carbon and farm size constraints suggests an informed respondent profile. Residual uncertainty over productivity during the transitional phase, however, remains a concern warranting evidence-based field demonstration, as noted by Eyhorn et al. (2019).

The positive bivariate correlations of annual income and landholding with attitude suggest that farmers possessing greater economic resources tend to hold more favorable attitudes toward natural farming. However, in the multivariate regression model, annual income did not emerge as a significant predictor, indicating that its influence may operate indirectly through other socioeconomic and motivational factors. In contrast, landholding remained a significant positive predictor, highlighting the importance of farm resource endowment in shaping attitudes toward natural farming. Achievement motivation emerged as a significant predictor, indicating that farmers with stronger aspirations for success and innovation are more likely to develop favorable attitudes toward natural farming. Although scientific orientation showed a significant positive correlation with attitude, its effect was not statistically significant in the regression model, suggesting overlap with other psychological variables included in the analysis. The positive attitude toward indigenous inputs Bijamrut, Jivamrut, Nimastra, and neem extracts corroborates the findings of Singh and Patel (2021) and reflects the effectiveness of KVK-led training in building familiarity with on-farm input preparation.

The significant negative correlations of age and farming experience with attitude are consistent with the innovation diffusion literature, whereby older and more experienced farmers exhibit greater habit persistence in conventional high-input systems (Thangjam & Jha, 2024). The negative association of extension contact with attitude may reflect the historical orientation of extension services toward conventional input-intensive agriculture, which may have reinforced conventional farming norms. The non-significant association of education with attitude likely reflects the narrow educational range within the sample. The negative regression coefficient of environmental orientation ($b = –0.249$) despite its positive bivariate correlation reflects a suppression effect in the multivariate context, as explained in the results section above.

CONCLUSION

The study establishes that farmers in the Tarai region of Uttar Pradesh hold a predominantly moderate attitude toward natural farming, shaped primarily by economic capacity, psychological motivation, and social engagement rather than by formal education or extension contact alone. Landholding, achievement motivation, economic motivation, risk orientation, and social participation are the most consistent enablers of positive attitude, while older age, longer conventional farming experience, and residual uncertainty about productivity during the transitional phase are the primary

attitudinal barriers. The regression model explains approximately 70 per cent of attitudinal variation, confirming that a combination of economic empowerment and psychological strengthening is necessary for attitude change. Extension programmes targeting the Tarai region must integrate income-support mechanisms, peer-learning platforms, and long-duration demonstration plots to convert moderate attitudinal endorsement into sustained natural farming adoption.

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Ethical approval and consent to participate: Our study did not require ethical approval, and all the authors agree.

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Research Note

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Climate-induced Migration, Farmers' Perception and its Determinants in Bundelkhand Region of Uttar Pradesh

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HIGHLIGHTS

- Climate-induced migration is a reality in sampled villages and climate change as a key driver for food insecurity.
- The SEM results show that climate adaptation strategies have restricted food insecurity.
- Limited availability of non-farm employment opportunities in the villages further exacerbated the credit trap.

ARTICLE INFO

Keywords: Climate change, Adaptation strategies, Food insecurity, Migration, Structural equation model.

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ABSTRACT

The study aims to examine the extent and dimensions of climate-induced migration, adaptation strategies, and food insecurity in the Banda district, India. By using a systematic random sampling procedure, a total of 100 samples were collected from two villages (i.e., Banthary and Amlokhar) of Kamasin development block of the Banda district, India, in April 2026. Further, descriptive statistics and the structural equation model (SEM) were applied to analyse the data. The results indicate that climate change-induced migration has increased manifold. About 74.07 per cent of households have reported that due to crop failure, they are unable to pay loans. Limited water resources, a rise in temperature, and a lack of non-farm employment opportunities were major drivers of food insecurity in sampled villages. Therefore, farmers have adopted different adaptation strategies to overcome food insecurity. This study suggested that investment in agriculture and non-farm activities is vital for restricting climate-induced migration. Responsive, well-resourced public institutions must support community-led strategies.

INTRODUCTION

Climate migration can be slow-onset or fast-onset. Rapid-onset natural disasters such as floods and cyclones usually result in immediate evacuation of households. Slow-onset processes such as desertification, soil degradation and rising temperature erode livelihood opportunities over time. Slow-onset results in seasonal or circular migration in which mostly the male members of the household migrate to urban areas for work during agricultural off seasons and stay back in the village with family. Climate induced migration strongly interact with the socio-economic conditions of the community. Climate is seldom a single driver. Instead, it amplifies the already existing vulnerabilities of poverty, landlessness, unemployment and low access to credit or technology. Small and marginal farmers with limited land are more vulnerable to climate shocks because they cannot make investments in irrigation, crop diversification or climate resilient technologies. These households are therefore more prone to use migration as a coping mechanism. In addition, backward social groups and tribal farmers face have structural inequalities that further limit their adaptability (Jena & Kanungo, 2021).

Large scale migration occurs toward urban areas already facing infrastructure stresses, housing and public services crisis. Unplanned rapid growth of cities, strains resources resulting in

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informal settlements and water, sanitation and health systems, a complete set of policies and views on climate-induced migration can be tackled through mitigation, adaptation and development. Investing in climate-resilient agriculture, improving access to irrigation and diversifying income sources help in reducing the vulnerability of rural livelihoods (Pal et al., 2017; Roy et al., 2022). Social protection measures, such as employment guarantee schemes and crop insurance, can help mitigate the impact of crises when they are available during crises. Education, skill development and access to information can increase people's ability to migrate safely and productively when they need to do so (Jena & Aditya, 2022). Urban planning and governance must also prepare for rising numbers of migrants by providing sufficient housing, infrastructure and employment. Migration should not only be viewed as a problem, but also as an adaptive response to climates stresses.

Drought in semi-arid areas has been one of the strongest factors of migration in India (Singh, 2020). Drought is one of the strong causes of migration as the deficiency of soil moisture and water availability do much harm to the farming (Singh et al., 2020; Sreekumar & Sabuj, 2024), as India has 93 per cent of the population and 87 per cent of the districts that are drought moderate to very highly vulnerable. In the semi-arid tropics, around 69 per cent of households are vulnerable to drought, which significantly raises the chances of labour migration (Pradhan & Narayanan, 2020). Moreover, historical data indicated that heat waves and other climate disasters have increased in intensity in India over the years (Moharaj et al., 2025), causing large-scale displacement. In India, a total of 56.23 million internal displacements have occurred from 2008 to 2023 (IDMC, 2023). Most of these migrations are quick and involuntary, which makes handling them even more difficult.

METHODOLOGY

The present study uses systematically collected field survey data from the Banda district of Uttar Pradesh in April, 2026. The district is climatologically in a semi-arid to sub-humid zone. It is characterized by drastic changes in temperature, whereby the hottest summers reach 47°C and the southwest monsoon is very unpredictable. In Banda, the rural poor have made migration an unavoidable part of their livelihood approach due to the mounting pressures of climate change impacts such as escalating temperatures, erratic rainfall, pest attacks, and subsequent economic deprivation. The type of migration which is actually distress migration due to extreme economic deprivation, natural calamities, and intolerable social conditions of the place of origin and not due to "pull" of urban aspirations (Anuja et al., 2018). To capture grassroots information on farmers' perceptions of climate-induced migration and their determinants, Kamasin Development Block was chosen. The Kamasin is plagued by gross infrastructural shortages, especially in water management and connectivity. In the Kamasin Development Block, two villages, namely Banthary and Amlokhar, were chosen for the household survey. Both the villages have very traditional, agrarian characteristics. Lastly, fifty sample farmers were selected from each village for a household-level survey. Thus, one district, one development block, two villages, and 100 samples were collected to capture a comprehensive picture of climate-induced migration in the Bundelkhand region of Uttar Pradesh.

In order to analyse the data, the Structural Equation Model (SEM) was used to investigate whether food insecurity acted as a mediator in the relationship between climate change adaptation strategies and climate migration (Pearl, 2012). Further, SEM is used to examine whether the relationship between an independent variable (X) and a dependent variable (Y) is influenced partially or fully by a third variable called the mediating factor (Z). The model can be expressed through the following equation:

$$X = \beta_0 + \varepsilon_1 \quad \text{... (1)}$$

$$Z = \delta_0 + \gamma X + \varepsilon_2 \quad \text{...(2)}$$

$$Y = \eta_0 + \beta X + \varphi Z + \varepsilon_3 \quad \text{...(3)}$$

Where X represents the climate change adaptation strategies; Z represents the food security; represents the climate migration; β_0, δ_0 and η_0 represents the regression intercepts; γ, β and φ are the estimated coefficients; and ε_1, ε_2 and ε_3 are the uncorrelated error terms with a mean of zero. The study also computed the conditional expectation to assess the total effect, yield and conditional expectation $E(\{Y \mid x, Z\} = \eta_0 + \beta X + \varphi Z)$. In fact, it (E) was used to evaluate the overall causal impact of changing the independent variable (X) from one baseline value (x) to new value (x′) on the dependent variable (Y), while accounting for both direct and indirect effects influence by mediating factor (Z). this compares outcomes when X changes from a baseline value (x) to a new value (x′). From this, study derived the indirect effect as follows:

$$IE(x,x') = \Sigma z(\eta_0 + \beta X + \varphi Z)\ [P(Z \mid x') - P(Z \mid x)] = \varphi[E(Z \mid x') - E(Z \mid x)]) \quad \text{... (4)}$$

Where IE is the indirect effect; and P is the pre-transition distribution. Equation 4 can be simplified as follows:

$$IE(x,x') = \gamma\varphi(x' - x) = (x'-x)\ (t-\beta) \quad \text{...(5)}$$

Where, *t* represents the slope of the total effect, which can be calculated as follows:

$$t = \frac{E(Z \mid x') - E(Z \mid x)}{x' - x} = \beta + \gamma\varphi \quad \text{...(6)}$$

This study derived standard expressions for indirect effects within linear systems, which can be estimated as the difference t - β or as the product $\gamma\varphi$ (Pearl, 2012).

RESULTS

Extent and dimensions of migration in Banda

Figure 1 shows the reasons that motivate sampled households to migrate to nearby urban areas. From post-Green Revolution, it is very visible that the cost of cultivation has been increased manifold. Therefore, farmers needed additional funds and resources to continue farming, and once crop failure occurred due to a rise in temperature, farmers were not in a position to pay loans. This is clearly visible in the sampled villages. About 74.07 per cent of households have reported that due to crop failure, they are unable to pay loans. Limited availability of non-farm employment opportunities in the villages further exacerbated the credit trap. With

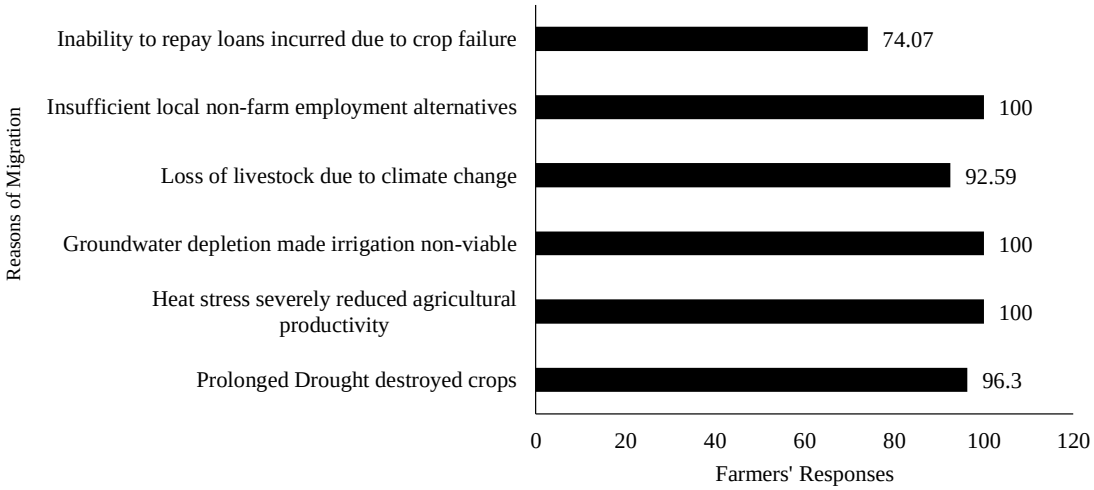


Figure 1. Reasons for Migration in the Surveyed Villages

limited water availability along with grazing land, livestock lost their lives, which are a secondary source of income in the area. Further, the majority of the households have reported that heat stress has depleted both surface and groundwater resources, which is responsible for crop productivity losses in the area.

Extend and dimensions of food insecurity in Banda

Crop failures in the sampled villages were caused by climate change and resulted in food insecurity in the area. In order to understand the depth and breadth of food security, some passive reasons were identified, and the responses of farmers were recorded to understand why food suppliers have become food importers (see Table 1). Responses were rated on a Likert scale ranging from "never", "rarely", "sometimes" and "often". As seen in Table 1, more than half of the sample households reported concerns of food availability resulting in restrictions in their consumption of preferred foods. Around 30 per cent of the surveyed households reported frequently eating a narrow range of food, which is a main factor in nutritional food insecurity. Similar statistics can also be seen in "no food to eat at home" and "eating fewer meals per day."

Climate adaptation strategies adopted by sampled households

Table 2 depicts climate adaptation strategies adopted by the sampled households in surveyed villages. As the Banda district has a dry climatology, most adaptation strategies are about how to conserve soil and water resources. Hence, adopted strategies were classified into three categories, namely economic, irrigation management, and sustainable development-oriented strategies.

Table 2. Identified climate adaptation strategies in surveyed villages

Factors	Positive response
Economic Strategies	
Non-agricultural activity outside the farm	35.25
Non-agricultural employment	20.75
Getting a loan	80.00
Using personal savings	90.25
Reduced household expenses	12.25
Livestock sale	85.25
Irrigation management strategies	
Irrigation pattern change	60.25
Improving the coverage of water transmission channels	75.25
Use of alternative water sources	80.25
Management of irrigation intervals	65.00
Watershed management activities	80.00
Sustainable development-oriented strategies	
Changing the crop cultivation deadline	56.25
Conservation tillage	45.25
Agricultural land levelling	20.25
Changing the time of crop harvest	45.25
Multi-cropping	80.00
Compliance with crop rotation	12.25
Reducing the distance between crop rows	25.00

Source: Field Survey, 2026.

As far as economic strategies were concerned, about 35.25 per cent of households were engaged in non-agricultural employment activities, and among them, 20.75 per cent got employment. About 80 per cent of households have taken out loans for agricultural

Table 1. Food insecurity access in the sampled households

Indicators	Never	Rarely	Sometimes	Often
Worrying about food availability	20.25	16.5	40.5	22.75
Unable to eat preferred food	26.5	19.5	34.5	19.5
Eating a limited variety of food	15.25	17.5	37.75	29.5
Eating unappealing food due to lack of alternatives	10.25	10.5	47.25	32
Eating a smaller meal	5.5	12.5	50.75	31.25
Eating fewer meals in a day	15.75	9.25	50.25	24.75
No food to eat at home	18.5	19.5	50.25	11.75
Not eating for a whole day and night	7.5	45.5	40.25	6.75

purposes, while more than 90 per cent of households have used personal savings, followed by 12.25 per cent who have reduced their expenditure and 85.25 per cent who have sold their livestock to secure their livelihoods and to mitigate adverse effects of climate change.

Further, as water is vital in an agrarian economy, more than 60 per cent of households have adopted various water conservation techniques. About 75.25 per cent of households have improved the coverage of water transmission channels by making concrete canal channels to reduce water loss. In the sampled villages, ponds were constructed under MGNREGA; therefore, households have multiple resources of irrigation, i.e., canals, ponds, and tube wells. Hence, more than 80 per cent of households have used multiple irrigation channels. These multiple irrigation sources enhanced irrigation resilience in the study area.

Lastly, sustainable development strategies were also adopted by the households. For instance, 56.25 per cent of households have changed the crop cultivation deadline by growing early maturing varieties, followed by 45.25 per cent who have adopted tillage conservation techniques, 20.25 per cent who have levelled the field, 45.25 per cent who have changed harvesting time, and 80 per cent who have diversified their cropping pattern within the cropping season.

Relationship between climate adaptation strategies, migration and food insecurity

Table 3 illustrates the substantial direct and indirect consequences of various climate adaptation measures, climate-induced migration, and food insecurity. The research indicates that economic strategies directly influence climate migration, hence affecting migration patterns. Furthermore, an indirect effect is shown, demonstrating that economic strategies influence climate migration via other migration-related processes. The results demonstrate a clear correlation between economic strategies and food insecurity; specifically, improved economic strategies correlate with reduced levels of food insecurity.

The management of irrigation is especially critical in dry locations like Bundelkhand. The structural equation model (SEM) research indicates significant negative direct and indirect effects of irrigation management practices on climate migration. This indicates that effective irrigation management may mitigate climate-induced migration. The research indicated a direct impact of sustainable development initiatives on climate migration, but the indirect effect was negligible.

The cumulative impact of these measures on climate migration was not substantial, suggesting that while a direct negative correlation exists, the overall effect may be minimal. Strategies focused on sustainable development directly impact food insecurity, indicating a significant connection.

Moreover, food insecurity directly influences climate migration, indicating that increased food insecurity correlates with heightened climate migration. These findings underscore the intricate relationship among climate adaption measures, migration, and food insecurity, emphasizing the need for focused interventions in the examined locations.

DISCUSSION

The interplay between food insecurity and migration is intricate, bidirectional, and context-dependent, influenced by a confluence of environmental, economic, and political elements (Bardsley & Hugo, 2010). Climate shocks, like droughts and erratic rainfall patterns, directly jeopardize agricultural output and rural livelihoods, prompting communities to relocate in pursuit of more stable living conditions (FAO, 2016). Simultaneously, migration can exacerbate food insecurity by altering agricultural systems and generating population imbalances in impacted regions. In the Bundelkhand region, climate-induced migration functions as coping strategy. Migration can serve as an adaptive response to food insecurity, allowing households to diversify income sources and receive remittances that improve food purchasing power, healthcare, and education (Mekonnen et al., 2022). Research from West Africa and Uganda which are similar geographical conditions as in Bundelkhand region, indicates that remittances can mitigate the effects of climatic shocks and enhance household resilience (Osei-Amponsah et al., 2023). Involuntary or mismanaged migration can intensify vulnerability in both the origin and host regions. Limited absorption capacity in host communities often leads to competition

Table 3. The structural equation model results

Factors	Factor	Effect pathway	Original sample	Sample mean	t-statistic
Economic strategies	Climate migration	Direct effect	-0.026	-0.027	4.715*
		Indirect effect	-0.009	-0.010	4.68*
		Total effect	-0.050	-0.40	4.52*
	Food insecurity	Direct effect	-0.055	-0.060	4.48*
Irrigation management strategies	Climate migration	Direct effect	-0.191	-0.201	2.45**
		Indirect effect	0.025	-0.025	3.500*
		Total effect	-0.225	-0.235	2.775*
	Food insecurity	Direct effect	-0.180	-0.151	2.275**
Sustainable development-oriented strategies	Climate migration	Direct effect	-0.055	-0.059	3.660*
		Indirect effect	-0.005	-0.005	0.355^{NS}
		Total effect	-0.050	0.060	0.860^{NS}
	Food insecurity	Direct effect	-0.025	-0.029	3.645*
Food insecurity	Climate Migration	Direct effect	0.135	0.130	2.250**

Note: * & ** indicates 1%, 5% level of significance, while NS indicates non-significance.

for scarce resources, higher food prices, and social tension (FAO, 2016).

A holistic food and livelihood policy in an agrarian economy must consider the nexus of climate change, migration and food insecurity. The findings of this study are consistent with the findings of Reza et al. (2025). Their study shows that climate change adaptation strategies can strengthen community resilience but their effectiveness is highly dependent on the level of food insecurity. They also found that climate-related disasters very probably caused displacement. Sabbatasso et al. (2025) studied the situation in Guatemala and highlighted two major concerns: (i) the exacerbation of food insecurity due to climate change and the expansion of monoculture farming, and (ii) the insufficient institutional response to the interlinked crises. Suza et al. (2026) investigated the links between climate, livelihood insecurity and violent conflict in the context of access to fishing in coastal Bangladesh. They found that the climate patterns that affect fish populations and availability are exacerbating existing vulnerabilities, a trend observable across Bangladesh. Climate impacts, poverty, limited access to credit and weak governance interacted to render small-scale fisher livelihoods more vulnerable to stresses.

CONCLUSION

The study highlighted the linkages between climate change, migration and food insecurity in one of the most vulnerable region to climate change. The MGNREGA as the most popular strategy supports as institutional buffer against climate induced collapse of income. Access to institutional credit and direct income support reduces the risk of financial problems and the need to move. The coverage of Kisan Credit Card (KCC) should be extended to all agricultural households and a specific KCC product should be evolved for marginal farmers with lower rates of interest and flexible repayment linked to crop seasons. Priority should be given to self-help group (SHG)-bank linkage programmes for women farmers to enable the poorest to access credit. Policies should shift from trying to eliminate it to managing it to optimize its developmental benefits and to minimize its social costs. Bundelkhand Labor Mobility Program should be established, offering migrant workers portable social security, skills with certification, and housing support in the destination city.

DECLARATIONS

Ethics approval and informed consent: Informed consent was sought from the respondents regarding the study during the course of the data collection.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

The authors declare that during the preparation of this work, they thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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Research Note

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Determinants to Behavioural Intention of Fish Farmers to Adopt Carp Polyculture

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HIGHLIGHTS

- Theory of planned behaviour (TPB) was applied to understand people's intention to adopt composite carp culture and its determinants.
- Majority of the farmers were found in medium level of behavioural intention and the farmers' intentions were significantly shaped by perceived usefulness, ease of implementation, economic benefits, social influence, access to technical knowledge, and institutional support.

ARTICLE INFO

Keywords: Fish farmers, Carp polyculture, Behavioural intention, Adoption, Productivity.

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ABSTRACT

The study was carried out in Ganjam district of Odisha to measure the behavioural intention of the fish farmers to adopt composite carp culture with the objective of assessing the determinants to behavioural intention of fish farmers to adopt carp culture. Both purposive and random sampling procedures were followed in selecting 120 respondents. Data were collected through pre-tested structured interview schedule during 2023-24. Majority of the farmers were found in medium level of behavioural intention followed by high- and low-level behavioural intention. Seven variables such as area under fish farming, information source utilization, participation in extension activities, innovativeness, risk preference and economic motivation showed a highly significant and positive relationship with the behavioural intention of fish farmers. Strengthening extension facilities to ensure effective monitoring and follow up farmers, conducting training programmes focused on scientific and technical knowledge related to carp culture, improving the execution of existing fishery development schemes, developing a comprehensive disease management plan and encouraging more number of fish farmer producer organisations were the suggestions in order to improve the overall productivity and sustainability of composite carp culture, ultimately benefiting farmers and enhancing their livelihoods.

INTRODUCTION

The fisheries sector, contributing about 6.72 per cent to the agricultural GVA with a compound annual growth rate of 8.9 per cent between 2014-15 and 2022-23 is crucial to the Indian economy. The sector provides livelihood to about 30 million fishers and fish farmers at the primary level and twice the number along the value chain (MoFAHD, 2026). Indian fisheries in context of inland fisheries have witnessed a paradigm shift through emerging as a major contributor of fish production from 36% in the mid-1980 to 70% in the recent past (Shasani et al., 2020). Diverse geographically in many aspects, Odisha have 7.04 lakh Ha of freshwater resources, 4.18 lakh ha of brackish water resources and 480 Kms. of coastline. Odisha is one of the major fish producing states and ranks 4th in total fish production in India after Andhra Pradesh, West Bengal and Karnataka (MoFAHD, 2023-24). There is a four-fold increase in total fish production in the state over the last 21 years. Among the 33 districts of Odisha state, Ganjam district contributes 5525

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MT of fish from 1929.24 ha of water area in terms of pond and tanks and is considered to be one of the potential aquaculture resources districts of the state. Being a resource rich district, it provides an excellent employment opportunity to rural poor and to meet the growing demand for fish. Despite several efforts, the adoption rate is beyond governmental expectations. Adoption of scientific fish farming practices by the farmers is of paramount importance for bridging this gap (Varshney et al., 2020). The recent measures therefore have targeted intensive aquaculture in ponds and tanks through integrated fish farming, carp polyculture and running water fish culture (DADF, 2019). Composite carp culture is defined as the culture in which more than one type of compatible fishes is cultured simultaneous and it enables to get maximum fish production from a pond through utilization of available fish food organisms in all the natural niches. Depending on the compatibility and type of feeding habits of the fishes, it involves stocking of Indian major carps (IMCs) such as catla (*Catla catla*), rohu (*Labeo rohita*), and mrigal (*Cirrhinus mrigala*) as well as three other exotic carps *viz*, silver carp (*Hypophthalmichthys molitrix*), grass carp (*Ctenopharyngodon idella*) and common carp (*Cyprinus carpio*). These three IMCs contribute the major chunk of the freshwater aquaculture production followed by the exotic carps forming the second important group (Rutayisire et al., 2017). It is crucial to gain a deeper understanding of how to motivate farmers to adopt fish production. Identifying the socio-psychological factors and beliefs that influence farmers' intentions to engage in fish farming can offer valuable insights. These insights can guide the development and refinement of existing policies to better support adoption efforts. With this objective, the study has been undertaken.

METHODOLOGY

The study was carried out in Ganjam district of Odisha. Ganjam district was selected purposively for being one of the top potential fishery districts of the state contributing 8-9% of fish production of the state (MoFAHD, 2023-24). Ganjam district comprises of twenty-two community development blocks out of which three blocks namely Chhatarpur block, Bhanjanagar block and Purushottam block were selected on random sampling basis and five villages from each block were selected randomly; thus, a total of 15 villages were covered. From each village (15 villages), 8 farmers were chosen as respondents following random sampling technique making total 120 respondents for the present study. Primary data were collected through a pre-tested structured interview schedule. This study uses the theory of planned behavior (TPB) to understand farmers' motivation to adopt fish production. TPB offers an empirically supported framework where intention is the main predictor of behavior (Ajzen, 2012 & Hagger et al., 2018). Intention is influenced by three factors: attitude (positive or negative evaluation of the behavior), subjective norms (perceived social support), and perceived behavioral control (belief in one's ability to perform the behavior). This helps explain what drives farmers to engage in fish production. The TPB postulates that to change behaviour, beliefs underlying that behaviour need to be changed (Ajzen & Schmidt, 2020). Specifically, those beliefs that are most salient for people are the best candidates to address in an intervention targeted to change behaviour, because salient beliefs are the considerations that lead people to engage or not engage in a particular behaviour (Yzer & Gilasevitch, 2019). Hence, identifying the salient behavioural beliefs, normative beliefs and control beliefs that represent factors that would facilitate farmers to adopt fish production is of vital importance. Seventeen statements were taken under the five components of intention, attitude, subjective norm, perceived behavioural control and self-identity following the scale developed by Silva et al. (2020). The farmers were asked to respond to each statement in a 5-point continuum, the frequency was recorded. The mean score was then worked out and presented in Table 1. The range of behavioural intention score was from 17 (Minimum score) to 85 (Maximum score). For each respondent, the total score was calculated and it was divided into three categories using arbitrary method. The categories are i.e. low (d"67 score), medium (67-75 score) and high (e"75 score). The respondents were categorized accordingly.

RESULTS

Behavioural intention of fish farmers

Behavioural intention of fish farmers reflects the extent to which individuals were motivated to perform a given behaviour and was conceptualized as the most proximal antecedent of behaviour. It is believed that behavioural intention is one of the important factors to accelerate the farmers to adopt new technology. It was observed from Table 1 that attitude plays a vital role in shaping the behavioural intention of the farmers with highest average mean score 4.31 while majority of respondent have agreed with the statement that "adopting carp polyculture is more advantageous than monoculture" (mean score 4.54) and ranked I from the statements of attitude category which is important to motivate the farmers to adopt composite carp culture. Intention serves as the immediate precursor to the actual behaviour of farmers with average mean score 4.29 where majority of the fish farmers have agreed with the statement that they intend to adopt fish production in the next years. As per the respondent farmers, self-identity also plays a vital role, which refers to how individuals perceive themselves in relation to a specific behaviour, it encompasses the personal beliefs and self-conceptions that influence their intentions to engage in that behaviour, with average mean score of 4.12. The other factors influencing the behavioural intention were Subjective Norm and Perceived Behavioural Control with average mean score of 3.90 and 3.85 respectively.

Level of behavioural intention of the respondents

The range of behavioural intention score was from 17 to 85. For each respondent, the total score was calculated and it was divided into three categories using arbitrary method. The categories are i.e. low (≤67 score), medium (67-75 score) and high (≥75 score). The respondents were categorized accordingly and is presented in the table below. It is depicted that, 46.66% of the respondents had medium level of behavioural intention followed by 41.67% respondent farmers having high level and 11.67% having low level behavioural intention respectively.

Table 1. Behavioural Intention of fish farmers

Item	Statement	Mean Score	Rank
INT1	Do you plan to start producing fish in the upcoming years?	4.38	I
INT2	How much sure is your intention for carp polyculture in the next years?	4.23	III
INT3	How likely is it that you will adopt carp polyculture in the next years?	4.28	II
	Average mean score	4.29	
ATT1	Adopting carp culture is more advantageous than monoculture.	4.54	I
ATT2	Carp polyculture is a viable business with tangible results.	4.52	IV
ATT3	In carp polyculture the resources are used efficiently.	4.09	III
ATT4	Carp polyculture addresses food insecurity.	4.11	II
	Average mean score	4.31	
SN1	The majority of your important people believe that you should start carp polyculture in the coming years.	4.14	I
SN2	The majority of people whose opinions you respect would be in favor of you adopting carp polyculture in the upcoming years.	4.08	II
SN3	In the coming years, the majority of farmers like you will switch to carp polyculture.	3.39	IV
SN4	The adoption of fish production in the upcoming years would be approved by those involved in the fish supply chain.	4.00	III
	Average mean score	3.90	
PBC1	Adopting carp polyculture in the next years is completely up to you.	3.93	III
PBC2	You have the ability to adopt carp polyculture in the coming years.	4.15	II
PBC3	You possess adequate resources (financial and knowledge) to support fish production during this period.	4.23	I
PBC4	It is very easy to adopt fish production in the next years.	3.09	IV
	Average mean score	3.85	
SI1	You picture yourself as a fish farmer in the future.	4.00	II
SI2	Becoming a fish farmer is a key part of your goals and dreams for what lies ahead.	4.25	I
	Average mean score	4.12	

N: B- *INT- Intention, *ATT- Attitude, *SN- Subjective Norm, *PBC- Perceived Behavioural Control, *SI- Self Identity

(Max-5, Min-1)

Relationship of behavioural intention with the selected independent variables

The relationship between selected socio-economic characteristics of fish farmers and their behavioural intention was worked out by correlation coefficient and the computed 'r' values are presented in Table 2. The table indicates that six variables such as area under fish farming (X_6), information source utilization (X_8), participation in extension activities (X_{10}), innovativeness (X_{11}), risk preference (X_{12}) and economic motivation (X_{14}) showed a highly significant and positive relationship at 5% level whereas, scientific orientation (X_{13}) and knowledge level (X_{15}) showed significant and positive relationship at 1% level. Information sources utilization of the fish farmers had a positive and significant correlation with the behavioural intention. Six variables such as education (X_2), family type (X_3), family size (X_4), experience in fish farming (X_5), Annual income (X_7) and social participation (X_9) were found to have non-significant relationship. Age (X_1) was found to have a negative as well as significant relation-ship with the behavioural intention of fish farmers.

DISCUSSION

From the behavioural intention of the farmers, it is observed that attitude of fish farmers plays a crucial role in their behavioural intention to adopt composite carp culture, with the ranking of attitudes as the most influential factor. As the strong positive attitude among fish farmers regarding the advantages of adopting composite carp culture emphasizes the critical role of perception in shaping behavioural intention of farmers. The next most influential factor was intention which is defined as a person's readiness or willingness to perform a specific behaviour. As comparatively less farmers were agreed with these factors which having several

Table 2. Correlation analysis of selected independent variables with the behavioural intention of fish farmers to adopt carp culture

Independent Variables	Correlation Coefficient (r)
Age (X_1)	-0.238*
Education (X_2)	0.081 ^{NS}
Family type (X_3)	-0.195^{NS}
Family size (X_4)	-0.147^{NS}
Experience in fish farming (X_5)	0.264 ^{NS}
Area under fish farming (X_6)	0.302**
Annual income (X_7)	0.174^{NS}
Information source utilization (X_8)	0.367**
Social participation (X_9)	0.142^{NS}
Participation in extension activities (X_{10})	0. 561**
Innovativeness (X_{11})	0.576**
Risk preference (X_{12})	0.265**
Scientific orientation (X_{13})	0.321*
Economic motivation (X_{14})	0.483**
Knowledge level (X_{15})	0.615*

** Significant at 5% level of significance; * Significant at 1% level of significance, NS-non-significant

implications for the adoption of scientific practices in aquaculture, they might lack the motivation that require substantial time, effort, and resources. Similar findings were reported by Lokman et al. (2024); Tunca et al. (2024); Argade et al. (2023); Brugere et al. (2021) and Borges et al. (2019). Inviting successful local fish farmers to share their experiences can help create role models and inspire others. Establishing or strengthening local fish farming associations that encourage networking, collaboration, and collective learning. This can help farmers develop a sense of belonging and commitment to the profession. Similar findings were reported by Rise et al. (2010). Regarding the results from the association between selected independent variables and behavioural intention, Information sources utilization of the fish farmers had a positive and significant correlation with the behavioural intention. Fish farmers gained valuable knowledge about fish culture practices from various sources, which also helped them understand the important roles of training, credit, and subsidies. The behavioural intentions of the respondents were significantly influenced by their participation in extension activities. Farmers who engaged with social systems beyond their immediate environment had better opportunities to interact, exchange ideas, and share experiences with others (Niangati et al., 2025). Policymakers should prioritize strengthening extension channels and providing adequate resources to improve communication among fish farmers, thereby boosting productivity and promoting sustainability in the fisheries sector (Mondal et al., 2024). Innovativeness is linked to a person's willingness to embrace changes that lead to adopting new ideas and methods in scientific fish culture. People with a strong inclination toward innovation usually have a higher risk tolerance. It can be concluded that those who are more risk-oriented tend to adopt new practices more readily. Interestingly, fish farmers adopted scientific fish culture despite the inherent risks involved in the enterprise. A strong and significant positive relationship was found between economic motivation and the behavioral intention of fish farmers, which also encouraged other motives, including psychological ones, to adopt more productive and profit-driven strategies. This practice supports the efficient use of all ecological zones within the pond, enhances the maximum standing crop, and empowers rural youth, ultimately improving food and nutritional security (Prakash et al., 2018). The size of the pond significantly influenced the behavioural intention of fish farmers, indicating that larger water bodies encourage the adoption of scientific fish farming practices. Age showed a significant negative relationship with behavioural intention, as younger farmers were more enthusiastic and eager to learn and apply scientific technologies. The findings were in accordance with the findings reported by Goswami et al. (2012).

CONCLUSION

The findings revealed that farmers' intentions are significantly shaped by factors such as perceived usefulness, ease of implementation, economic benefits, social influence, access to technical knowledge, and institutional support. Farmers who perceive carp polyculture as a profitable and sustainable aquaculture practice are more likely to develop a positive intention toward its adoption. The study further highlights the importance of extension services, training programmes, and access to reliable information in enhancing farmers' confidence and willingness to adopt improved fish farming practices. Social networks and the experiences of fellow farmers also play a crucial role in influencing adoption decisions. The adoption of appropriate management and adaptation strategies in composite carp culture not only enhances farmers' economic well-being but also contributes to food security, rural development, and the long-term resilience of aquaculture systems.

DECLARATIONS

Ethical approval and consent to participate: Informed consent was obtained from all respondents prior to data collection.

Consent for publication: All participants provided their consent for the publication of the data included in this study.

Competing interests: The authors declare that they have no competing interests.

Conflict of interest: The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have critically reviewed, revised, and approved the manuscript and take full responsibility for its content.

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Constraints in Social Media use for Agriculture and Fisheries in Andhra Pradesh

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HIGHLIGHTS

- Fish farmers reported a higher total constraint intensity than farmers in agriculture.
- Barriers to support were most pronounced among agriculture farmers, particularly women and older farmers.
- Vernacular content and responsive online extension groups can enhance digital inclusion.

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Keywords: Agriculture farmers, Digital extension, Information credibility, Rural communication, Vernacular content, Social media.

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ABSTRACT

Social media has emerged as an important digital outreach tool to provide rural farming communities with timely agricultural and fisheries information. The study was conducted in 2025-26 in the Nellore and East Godavari districts of Andhra Pradesh to compare the constraints on the use of social media among agriculture and fish farmers. An ex post facto design was adopted, and data were collected from 80 agriculture and 80 fish farmers using a pretested, structured interview schedule. Four dimensions, access, usability, credibility, and social and institutional support, were identified, comprising twenty constraint statements. Respondents ranked these constraints, and severity was measured using the Rank-Based Quotient technique. The dimension with the most severe among fish farmers was usability, with a mean RBQ of 70.05. The non-availability of content in the preferred local language was the single biggest constraint for fish farmers (RBQ 84.50) and agriculture farmers (RBQ 79.50). The highest dimension of agriculture farmers was social and institutional support, with a mean RBQ of 60.5. The overall mean RBQ was higher for fish farmers (61.24) than for agriculture farmers (58.93). The inclusive digital extension requires vernacular, sector-specific content and responsive online extension support.

INTRODUCTION

The role of social media platforms such as WhatsApp, YouTube, and Facebook is emerging as a vital medium of communication in agriculture and fisheries. They help quickly spread advisory messages, facilitate farmer-to-farmer communication, share market information, and enable learning through short videos and live sessions. In India, with a comparatively low number of extension workers compared to the size of the farming population, digital platforms are seen as an adjunct to improve extension outreach (Nain et al., 2019; Shanmuka et al., 2022). Additionally, the availability of mobile Internet services and inexpensive smartphones has improved the ability to provide need-based, timely information in rural areas via social media platforms (Patel & Mallappa, 2022).

Previous studies show that social media has the potential to increase access to agricultural knowledge, enable two-way communication and provide opportunities for participatory learning

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within farming communities (Nain et al., 2019; Sandeep et al., 2022). However, just having access to the platform does not ensure effective use (Panda et al., 2019; Iwuchukwu et al., 2023). Some of the constraint's farmers face includes internet availability, device quality, lack of digital skills, language of the content, message relevance, information reliability, and farmers' feedback to the extension person (Guntukogula et al., 2023). The limitations diminish the utility of social media as an extension tool (Awuor et al., 2021). They can exacerbate inequalities between older and younger, male and female, less and more educated, less and more institutionalised, and those with and without social media experience (Kaur et al., 2022).

Successful Fish farming requires timely information on water quality, market prices, government schemes, feed management, disease symptoms, seed availability, and weather risks for successful fish farming. Many fisheries communities are situated in coastal, riverine, or pond-based systems with limited access to extension services (Shanabhoga et al., 2023). While digital platforms can mitigate distance constraints, fish farmers face challenges as fisheries content are less accessible than crop-related information. Additionally, a lack of scientific advisories in local languages exacerbates language barriers and terminology issues (Shivakumarappa et al., 2023).

Recent research on social media use in agriculture has identified several challenges, including poor connectivity, low digital literacy, misinformation, and a lack of locally relevant content (MadhuShekar et al., 2023). There is still limited comparative evidence of the differences between agriculture farmers and fish farmers in terms of these constraints. This comparison is important because the extension methods used for crop farmers may not suit the information needs and platform use conditions of fish farmers (Chowdary et al., 2024). The study hypothesised that the nature and intensity of constraints in the use of social media differ between agriculture farmers and fish farmers. The study aimed to identify, quantify, rank, and compare such constraints using the Rank-Based Quotient technique. This method was deemed appropriate because it transforms the respondents' "natural" ranking, enables comparison of the resulting percentage scores, and aids in prioritising constraints for extension planning. A focused comparison is therefore needed to identify areas where a common digital intervention is adequate and others where sector-specific support is required (Saha et al., 2024).

METHODOLOGY

The study was conducted in 2025–26 across 16 villages in the Nellore and East Godavari districts of Andhra Pradesh. An ex post facto research design was adopted because the study examined constraints that farmers had already perceived and experienced. The study was conducted in 2025–26 across 16 villages in the Nellore and East Godavari districts of Andhra Pradesh. Eight villages were selected from each district through purposive sampling from major crop-producing and fish-producing areas. Separate villages were selected for the agricultural and fisheries samples to ensure representation of both enterprise systems. From each selected village, 10 farmers engaged in the respective principal enterprise were selected. Thus, the final sample comprised 80 agriculture farmers from eight crop-producing villages and 80 fish farmers from eight fish-producing villages, giving a total of 160 respondents. Primary data were collected through a pre-tested structured interview schedule administered via personal interviews. Group discussions with farmers and local extension personnel were used only to understand the local context and refine the interpretation of the findings. The interview schedule consisted of 20 constraint statements grouped under four dimensions: access, usability, credibility, and social and institutional support. Each dimension comprised five statements. Respondents were asked to rank the five constraint statements within each dimension according to their perceived severity. The ranks were converted to Rank-Based Quotient (RBQ) values according to Sabarathanam (1988). RBQ values were calculated separately for each constraint statement within the four dimensions and for agriculture farmers and fish farmers. This technique was used to identify and prioritise the leading constraints within each dimension for the two groups. The findings were presented through constraint-wise RBQ values and ranks.

RESULTS

The ranking of individual constraints within the dimension revealed that each group of respondents faced several constraints, with different priority orders for them is presented in Table 1. For fish farmers, slow internet speed (RBQ = 65.25) was the most serious problem in the access dimension, while agriculture farmers ranked unreliable mobile internet as the most serious problem in the access dimension (RBQ = 64.00). Both groups identified high mobile data costs as the second greatest limitation to access, indicating that affordability remained a common barrier. The least significant access problem was network loss during working hours in the groups.

For the usability aspect, the unavailability of content in the preferred local language was the highest-ranked by the fish farmers (RBQ = 84.50) and the agriculture farmers (RBQ = 79.50). The second most severe fish farmer usability constraint (RBQ 82.75) and agriculture farmer usability constraint (RBQ 64.75) was trouble understanding technical terms without examples. Similarly, the constraints score was higher among fish farmers (69.50) than among agriculture farmers (59.25), indicating a greater device-related usability gap in fisheries.

The dimension of credibility as presented in Table 2, reveals that fish farmers considered the advice given late, not in time for the season or agro-climatic conditions, to be the main constraint (RBQ = 73.25), and agriculture farmers considered the main constraint as a mismatch of information with crop/fishery enterprise (RBQ = 75.25). On the support dimension, the highest RBQ was observed for the absence of official extension or farmer groups online among fish farmers (RBQ = 65.50), while barriers faced by women and older farmers were highest among agriculture farmers (RBQ = 70.75). The Dimension-wise Mean Values revealed that, among fish farmers, the most dominant constraint was usability (Mean RBQ = 70.05), whereas, among agriculture farmers, social and institutional support was the top one (Mean RBQ = 60.50). The Mean RBQ% for the overall constraint intensity was higher for Fish Farmers (61.24) than for Agriculture Farmers (58.93).

Table 1. Constraints in social media utilisation

S. No.	Constraint statement	Fishery		Agriculture	
		RBQ	Rank	RBQ	Rank
	Access				
1	Mobile internet was unreliable in the village	63.50	III	64.00	I
2	Slow speeds restricted videos or live sessions	65.25	I	48.25	IV
3	Network was lost during field hours	45.25	V	40.50	V
4	Power cuts restricted phone use	61.25	IV	59.75	III
5	Mobile data was too expensive	63.75	II	63.50	II
	Usability				
6	Suitable smartphone was not available	69.50	III	59.25	III
7	Installing or updating apps was difficult	56.00	V	40.50	V
8	Help was needed to manage accounts	57.50	IV	56.00	IV
9	Preferred local-language content was unavailable	84.50	I	79.50	I
10	Technical terms were difficult without examples	82.75	II	64.75	II
	Credibility				
11	Information did not match crop or fishery	64.25	II	75.25	I
12	Advice was not timely for season or agro-climate	73.25	I	66.25	II
13	Posts rarely showed prices or market demand	51.25	IV	50.00	IV
14	False or misleading advice was a concern	53.00	III	49.50	V
15	Credible pages or groups were difficult to identify	48.75	V	59.00	III
	Support				
16	Family discouraged social media use for farming	61.25	II	65.00	III
17	Women or older farmers faced more barriers	57.00	III	70.75	I
18	Official online extension group was absent	65.50	I	40.25	V
19	Extension officers rarely responded promptly	53.25	IV	66.25	II
20	Training on safe and effective use was unavailable	48.00	V	60.25	IV

Table 2. Mean constraint intensity by dimension

Constraint Dimension	Fishery		Agriculture		Difference
	RBQ	Rank	RBQ	Rank	
Usability	70.05	I	60.00	II	+10.05
Access	59.80	II	55.20	III	+4.60
Credibility	58.10	III	60.00	II	–1.90
Support	57.00	IV	60.50	I	–3.50
Overall mean	61.24		58.93		+2.31

Note: Positive difference indicates higher constraint intensity among fish farmers.

DISCUSSION

The results indicate that the profiles of constraints in the use of social media are shared to some extent, yet also sector-specific. The importance of vernacular content for digital extension effectiveness is evident from its unavailability in both groups. This finding aligns with other studies, which have found that language barriers and a lack of content in a region are significant barriers to farmers' uptake of social media (Malik & Ansari, 2024; Shanmuka et al., 2022). Compared to general agricultural information easily accessible on popular platforms, fisheries advisory information is less accessible, localised, and understandable to fish farmers than to other farmers.

Each group had a specific set of dominant credibility constraints. In fisheries, all decisions related to water quality, feed, disease, and harvest are time-sensitive, and the impact of untimely advice is magnified for the fish farmer. Farmers who received general advice on crop or fishery issues were less concerned about the discrepancy between what they were told and what they found in their fields. The above-mentioned trends are consistent with the previous studies, indicating that a social media-based extension service should be fast, relevant, credible and localised (Singh & Verma, 2023).

Supporting dimension further helps in understanding the relative pattern. The lack of institutional digital presence, as was the case with other extension groups, was the most frequently mentioned limitation to official support for fish farmers (Awuor et al., 2021). Fish farmers reported they lacked access to official support due to their lack of digital presence, specifically their official extension groups. However, farmers pointed to challenges faced by women and older farmers, helping shift the focus to the social dimension of the rural digital divide. The findings align with the literature, which indicates that gender, age, confidence, and household support influence participation in digital information systems (Eduafo et al., 2024). Thus, the use of social media for extension should not be restricted to delivering information. It should include digital literacy, inclusive training, vouching advisory teams and an open and responsive expert support (Sandeep et al., 2020). The results highlight the need for tailored, sector-specific content and immediate expert support to leverage social media effectively. Offering inclusive digital training to women, older farmers, and fish farmers can enhance access, trust, and the effective utilisation of online advisory services (Jarial & Sachan, 2021).

The study suggests that social media extension programs need to go beyond the dissemination of information and adopt a more targeted approach to providing digital support that is inclusive, needs-oriented, and sector-specific. For farmers, creating local-language fisheries advisories using simple examples, visual explanations, and prompt expert responses should be a priority. Digital extension interventions should place special emphasis on agriculture farmers, including women, older farmers, family members, and local extension workers, in training programmes to overcome social barriers (Jarial & Sachan, 2021). Creating official, online, verified groups at the village or block level can ensure information is credible and reduce reliance on unverified sources. Hence, cultivating digital literacy, vernacular content generation, and adaptive advisory services into the mainstream of extension work can turn social media into a more effective and accessible platform for agriculture and fisheries development, ensuring its greater reliability and engagement with social media users (Darshan & Meena, 2017).

CONCLUSION

The study shows that access, usability, credibility, and support-related factors are limiting the use of social media in the agriculture and fisheries sector, with varying degrees of severity across the study areas. The usability gap is larger for fish farmers, mainly because there is no easily understandable, local-language information about fisheries. The level of support constraints, particularly for women and older farmers in agriculture, is greater, and access to online responses is delayed. Results suggest that digital extension is not entirely about platform availability. For this to work, the content must be multilingual, focused on a specific sector, locally relevant and credible; the extension staff must be trained, and programmes on digital literacy must be inclusive. The usefulness of social media in agriculture and fisheries extension can be enhanced by clarifying the official online farmer group's role and improving response mechanisms.

DECLARATIONS

Ethics approval and informed consent: The study involved human participants and adhered to voluntary participation, informed consent, and confidentiality principles. No invasive procedure was involved.

Conflict of interest: The authors declare no conflicts of interest.

Authors' contribution: Sai Kumar Periginji: paper plan execution and manuscript preparation; Ajay Kumar Prusty, Pritam Tripathy: Monitoring, paper planning and manuscript editing; Biswajit Sahoo, Nibedita Mishra: Monitoring, manuscript editing and manuscript correction.

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