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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

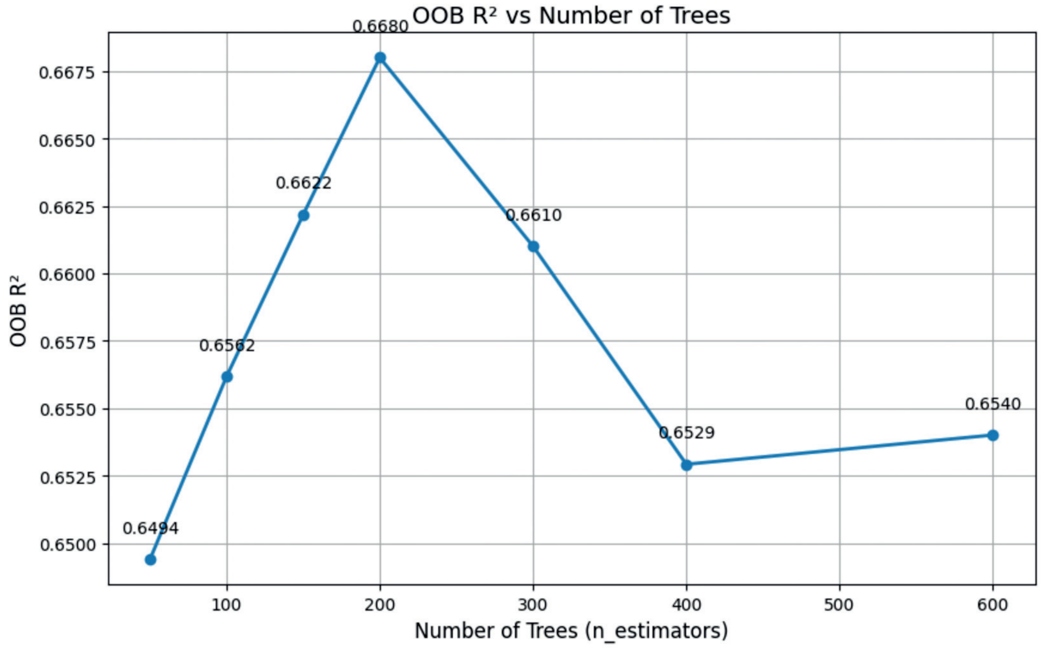


Figure 1. Out-of-Bag (OOB) R^2 versus Number of Trees in the Random Forest

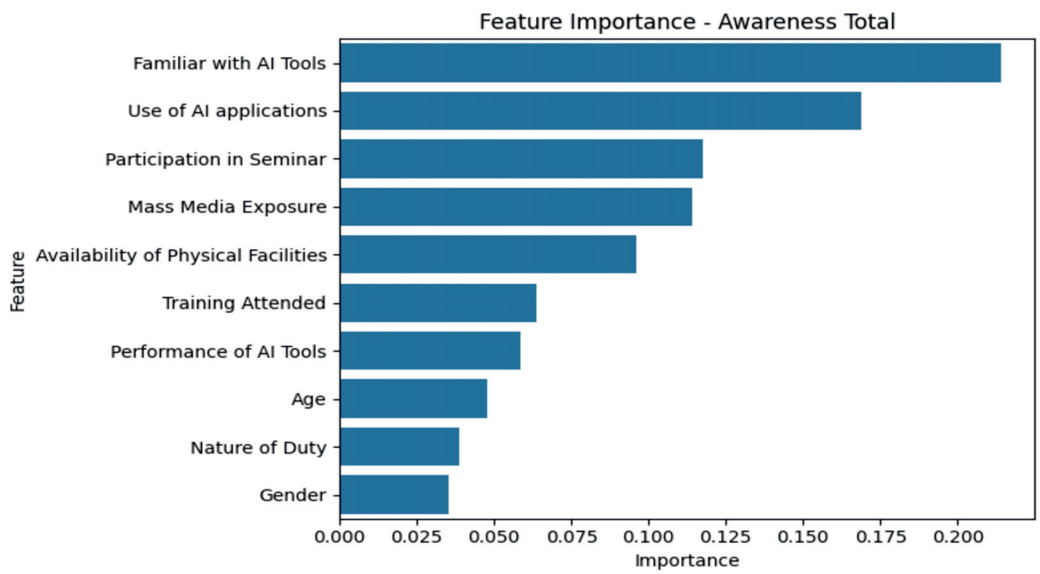


Figure 2. Permutation feature importance on the training set

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.

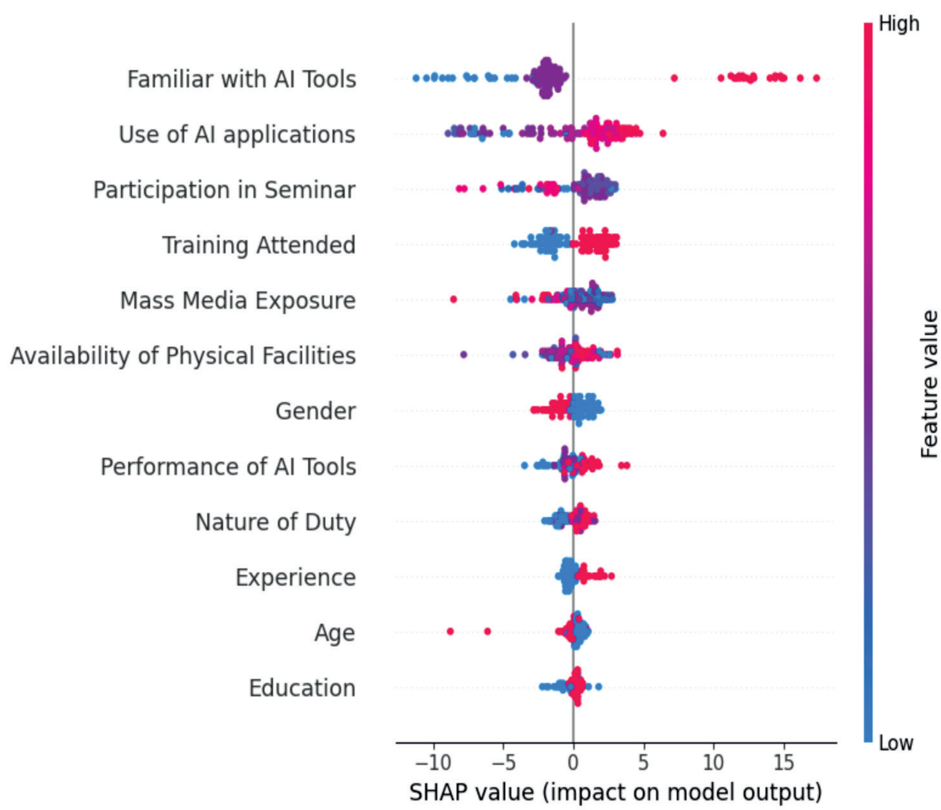
Demographic attributes such as Gender, Nature of Duty, Experience, Age and Education are some of the demographic attributes analyzed whose SHAP values were fairly concentrated around the zero-axis indicating their insignificance to the model predictions. While Age possessed some negative outliers reaching 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



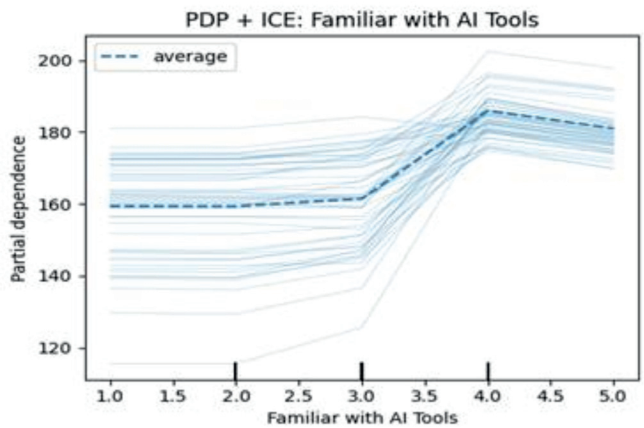


Figure 4a. Partial dependence with individual conditional expectation plot for Familiarity with AI tools

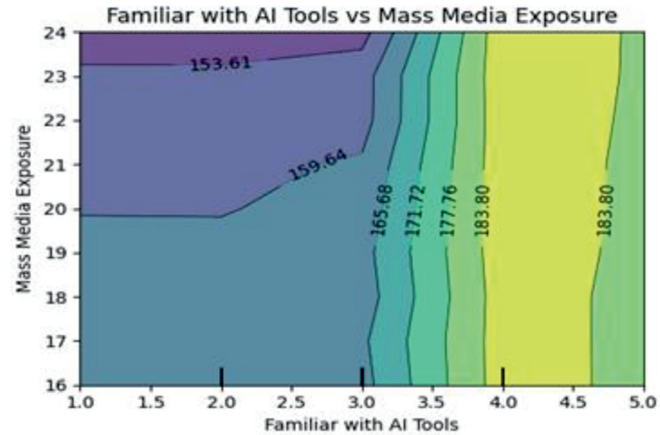


Figure 4b. Two-dimensional partial dependence of AI Awareness: Familiarity with AI Tools × mass media exposure

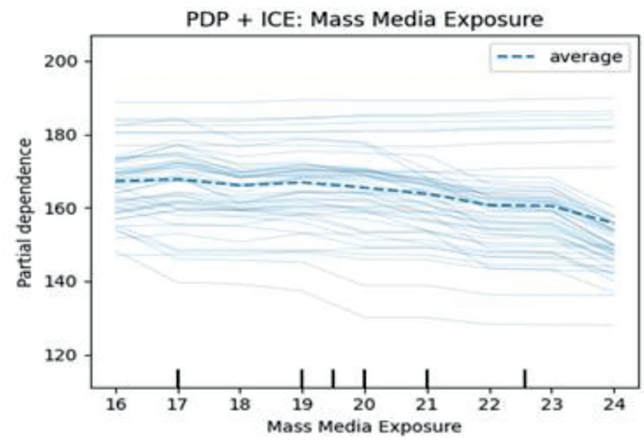


Figure 5a. Partial dependence with individual conditional expectation plot for mass media exposure

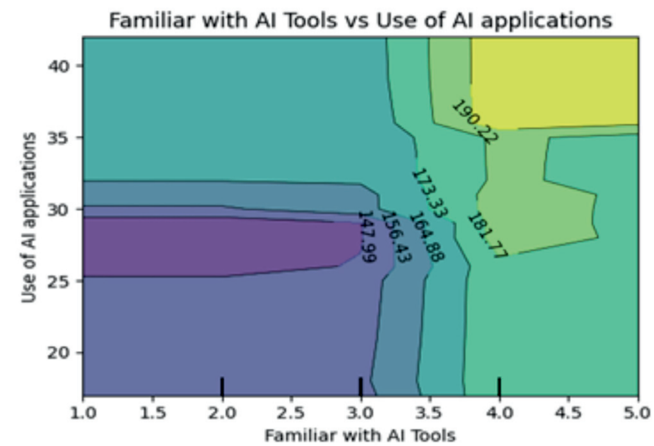


Figure 5b. Two-dimensional partial dependence of AI Awareness: Familiarity with AI Tools × Use of AI applications

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

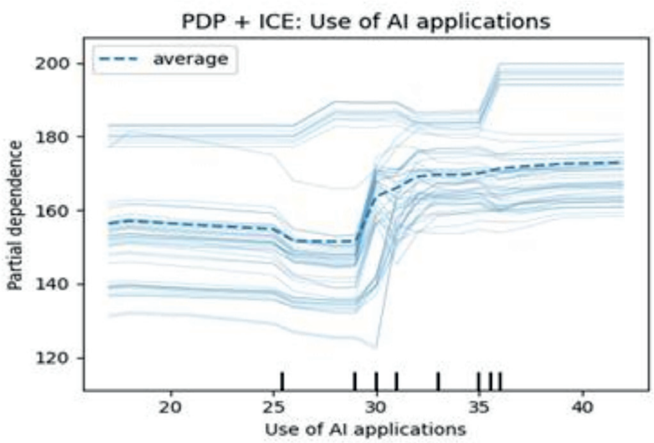


Figure 6a. Partial dependence with individual conditional expectation plot for use of AI applications

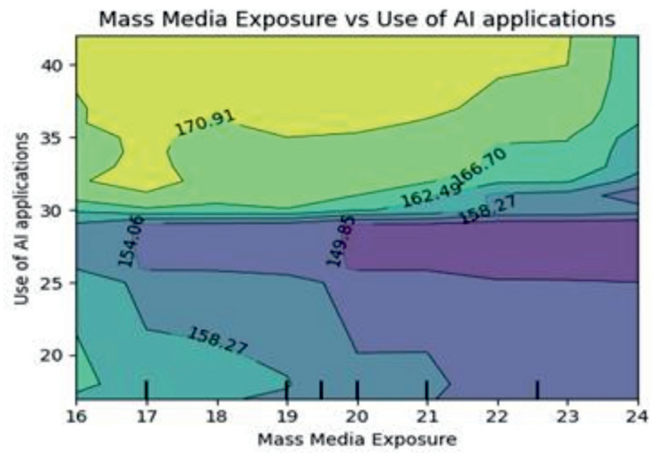


Figure 6b. Two-dimensional partial dependence of AI Awareness: Mass media exposure × Use of AI applications

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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REFERENCES

Barman, B., Singh, R., Padaria, R. N., Nain, M. S., Quader, S. W., & Praveen, K. V. (2026). A qualitative synthesis of barriers to agriculture 4.0 adoption: evidence from a systematic literature review. *Discover Agriculture, 4*, 34. https://doi.org/10.1007/s44279-026-00505-7

Chandra, S., Ghadei, K., Chennamadhava, M., & Ali, W. (2024). Development and validation of a farmer's focused digital literacy scale. *Indian Journal of Extension Education*, *60*(1), 111-115. https://doi.org/10.48165/IJEE.2024.601RT1

Devi, L. (2020). Awareness of livestock farmers on ICT tools. *Journal of Extension Education, 31*(3), 6357–6360. https://doi.org/10.26725/JEE.2019.3.31.6357-6360

Eli-Chukwu, N. C. (2019). Applications of artificial intelligence in agriculture: A review. *Engineering, Technology & Applied Science Research*, *9*(4), 4377-4383 https://doi.org/10.48084/etasr.2756

Ghosh, S., Kumar, A., Prusty, A. K., Naik, A., & Padhy, C. (2025). Modelling livelihood security of tribal farmers in South Odisha using machine learning. *Indian Journal of Extension Education*, *61*(4), 141-147. https://doi.org/10.48165/IJEE.2025.61423

Khanganbi, T. V., & Priya, M. (2024). Social media addiction among the rural youth: An AI interpretation. *Indian Journal of Extension Education, 60*(2), 52-55. https://doi.org/10.48165/IJEE.2024.60210

Kumar, A., Prusty, A. K., Naik, A., Kumar, N. P., Ojha, P. K., & Mounika, T. (2025). Adoption and compliance of AI enabled pest advisories: evidence from the national pest surveillance system (NPSS) in Odisha, India. *Indian Journal of Extension Education*, *61*(4), 78-83.https://doi.org/10.48165/IJEE.2025.61413

Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors, 18*(8), 2674. https://doi.org/10.3390/s18082674

Liu, J., & Wang, X. (2021). Plant diseases and pests detection based on deep learning: A review. *Plant Methods*, *17*, 22. https://doi.org/10.1186/s13007-021-00722-9

Naik, M. R., Apparao, C., Neelima, T. L., Teja, R. R., Singh, T., & Ramanjaneyulu, A. (2025). Digital agriculture and data-driven farming solutions for sustainable development. *Indian Farming*, *75*(12), 84-87. https://epubs.icar.org.in/index.php/IndFarm/article/view/173391

Niranjan, S., Singh, D. R., Kumar, N. R., Jha, G. K., Venkatesh, P., Nain, M. S., & Krishnakumare, B. (2023). Do information networks enhance adoption of sustainable agricultural practices? Evidence from northern dry zone of Karnataka, India, *Indian Journal of Extension Education, 59*(1), 86-91. http://doi.org/10.48165/IJEE.2023.59118

Panda, S., Modak, S., Devi, Y. L., Das, L., Pal, P. K., & Nain, M. S. (2019). Access and usage of Information and Communication Technology (ICT) to accelerate farmers' income. *Journal of Community Mobilization and Sustainable Development, 14*(1), 200-205.

Patil, M., Philip, H., & Sriram, N. (2018). Farmers' awareness level about ICT tools and services in Karnataka. *Journal of Extension Education, 29*(2), 5870–5874. https://doi.org/10.26725/JEE.2017.2.29.5870-5874

Rose, D. C., Wheeler, R., Winter, M., Lobley, M., & Chivers, C. A. (2021). Agriculture 4.0: Making it work for people, production, and the planet. *Land use policy*, *100*, 104933. https://doi.org/10.1016/j.landusepol.2020.104933

Ruzzante, S., Labarta, R., & Bilton, A. (2021). Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World development*, *146*, 105599. https://doi.org/10.1016/j.worlddev.2021.105599

Ryo, M. (2022). Explainable artificial intelligence and interpretable machine learning for agricultural data analysis. *Artificial Intelligence in Agriculture*, *6*, 257-265. https://doi.org/10.1016/j.aiia.2022.11.003

Saha, P., Prusty, A. K., Nanda, C., Ray, S., & Sahoo, B. (2024). Professional insights provided by women extension personnel in Odisha. *Indian Journal of Extension Education*, *60*(3), 101-105. https://doi.org/10.48165/IJEE.2024.603RN03

Sahoo, S., Parasar, B., & Jayasingh, D. K. (2025). Towards digitally enabled extension services: ICT training directions in coastal Odisha. *Indian Journal of Extension Education, 61*(4), 66–71. https://doi.org/10.48165/IJEE.2025.61411

Satapathy, G. P., Das, S., Sahu, B. L., Dash, S., & Tripathy, M. (2024a). Constraints of ICT adoption in agriculture in Khurda and Bargarh districts of Odisha. *Indian Journal of Extension Education*, *60*(3), 106-109. https://doi.org/10.48165/IJEE.2024.603RN04

Satapathy, G. P., Sarbani Das, & Maitreyee Tripathy. (2024b). Factors influencing ICT accessibility among the farming community of

Odisha. *Indian Journal of Extension Education*, *60*(2), 38-42. https://doi.org/10.48165/IJEE.2024.60207

Sebastian, A. J., & Jeyalakshmi, G. (2019). Use of digital tools for horizontal spread of agricultural technologies. *Journal of Extension Education, 31*(4), 6411–6416. https://doi.org/10.26725/JEE.2019.4.31.6411-6416

Shehrawat, P. S., Arulmanikandan, B., Singh, S., & Aditya. (2024). Farmers' awareness level and adoption regarding usage of ICT for crop production. *International Journal of Agriculture Extension and Social Development, 7*(11S), 167–173. https://doi.org/10.33545/26180723.2024.v7.i11Sc.1366

Singh, D., & Mathur, S. (2024). Consumption pattern of information and communication technology in agriculture. *Indian Journal of Extension Education, 60*(1), 128–131. https://doi.org/10.48165/IJEE.2024.601RN2

Singh, P., Jirli, B., Ghadei, K., Roy, P., & Kumari, J. (2023). Objectives of extension education: An analysis of perception of KVK professionals. *Indian Journal of Extension Education*, *59*(2), 74-78. http://doi.org/10.48165/IJEE.2023.59216

Sondarva, Y. M., Nain, M. S., Singh, R., Mishra, J. R., Singh, D. R., & Parsad, R. (2023). E-readiness assessment of national agricultural research system. *Indian Journal of Extension Education*, *59*(4), 82-85. https://doi.org/10.48165/IJEE.2023.59417

Suman, S., Prusty, A. K., Deb, A., Kumari, A., & Reddy, G. S. (2025). Global research trends in family farming: A bibliometric insight. *Indian Journal of Extension Education*, *61*(1), 25-31. https://doi.org/10.48165/IJEE.2025.61105

Talaviya, T., Shah, D., Patel, N., Yagnik, H., & Shah, M. (2020). Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*, *4*, 58-73. https://doi.org/10.1016/j.aiia.2020.04.002

Vikash. (2022). Impact of Artificial Intelligence on Agriculture Production, Practices and Management, (Unpublished Ph.D. Thesis). Chaudhary Charan Singh Haryana Agricultural University, Hisar, Haryana.