



Drivers of Farmers' Intention to Adopt Digital Platforms for Natural Farming Inputs in Andhra Pradesh

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HIGHLIGHTS

- Personal Innovativeness was the strongest driver of farmers' intention ($\beta = 0.483$; 100% normalized importance).
- Performance Expectancy, Facilitating Conditions, Effort Expectancy positively influenced farmers' behavioural intention.
- Perceived Cost, Perceived Risk and Social Influence showed no significant effect on behavioural intention ($p > 0.05$).
- SEM-ANN model explained 51.8% of the variance in behavioural intention, with all three analytical methods ranking Personal Innovativeness first.

ARTICLE INFO

Keywords: Natural farming, Behavioural intention, Unified theory of acceptance and use of technology, Structural equation modelling, Artificial neural network.

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ABSTRACT

The study examined the drivers of farmers' intention to adopt a Natural Farming digital input platform. The Unified Theory of Acceptance and Use of Technology was extended by incorporating Personal Innovativeness, Perceived Cost and Perceived Risk alongside Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions. Primary data were collected between July and November 2024 from 795 Natural Farming farmers across Andhra Pradesh, employing a structured questionnaire through direct interviews and supported by *Rythu Sadhikara Samstha*, the state nodal agency for Natural Farming. An integrated methodology combining a two-stage Partial Least Squares Structural Equation Modelling with an Artificial Neural Network approach, complemented by Importance Performance Map Analysis, was employed. Results showed a positive and significant influence of Personal Innovativeness, Performance Expectancy, Effort Expectancy and Facilitating Conditions on behavioural intention, explaining 51.8% of its variance, while Social Influence, Perceived Cost and Perceived Risk were statistically non-significant. The Artificial Neural Network sensitivity analysis confirmed Personal Innovativeness as the most important predictor. Strengthening rural digital infrastructure and designing intuitive regional-language interfaces could accelerate inclusive adoption intention among small and marginal farmers.

INTRODUCTION

Indian agriculture's growing dependence on chemical inputs since Green Revolution is widely linked to declining soil health and environmental harm (Balla & Goswami, 2022; Timilsina et al., 2025; Zhou et al., 2025). Natural Farming has emerged as a sustainable, chemical-free solution that relies on farm-level bio-inputs prepared

from cattle derivatives and locally available materials (Bharucha et al., 2020; Saride & Sharad, 2024). Natural Farming enhances soil fertility and microbial activity and lowers per-acre costs (Centre for Economic and Social Studies, 2019; Koner & Laha, 2021; Mastiholi et al., 2023).

In India, the practice extends over roughly 1.005 million hectares (NITI Aayog, 2025b). Within Andhra Pradesh,

approximately 630,000 farmers practise Natural Farming on 290,000 hectares under Andhra Pradesh Community Managed Natural Farming initiative, administered by *Rythu Sadhikara Samstha* (NITI Aayog, 2025a). Despite these efforts, its wider adoption remains limited, mainly because of substantial on-farm labour needed to prepare bio-inputs and the scarce supply of ready-made bio-inputs (Balla & Goswami, 2022; Kumar et al., 2025). A digital input-procurement platform can ease these constraints by aggregating seasonal demand, letting producers supply farmers who cannot self-prepare inputs and ensuring timely, quality supply. Comparable platforms have improved input access and service delivery for smallholders (Cimino et al., 2024; Morepje et al., 2024; Sharma et al., 2024). The conditions for such platforms are increasingly favourable, as 95.15% of villages are now covered by third- or fourth-generation mobile networks, together with widespread use of mobile phones among farmers (Press Information Bureau, 2024; Kumar, 2025).

Various methods and theoretical frameworks explain the intentions of farmers towards agricultural technologies, Theory of Planned Behaviour (Ajzen, 1991), Technology Acceptance Model (Davis, 1989) and Unified Theory of Acceptance and Use of Technology, commonly referred to as UTAUT (Venkatesh et al., 2003) are among them. The UTAUT combines Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions to shape behavioural intention, and has been widely applied in agriculture to study digital advisory services (Cimino et al., 2024), precision agriculture (Larasati et al., 2024), digital literacy among tea growers (Lin et al., 2023) and fintech uptake (Sharma et al., 2024). The original UTAUT omits context-specific factors important for small and marginal farmers, so it is augmented here with Personal Innovativeness, Perceived Risk and Perceived Cost to better explain platform adoption in rural India (Al-Saedi et al., 2020; Shi et al., 2022; Upadhyay & Kaur, 2026) and is analysed through a two-stage Structural Equation Modelling–Artificial Neural Network (SEM–ANN) procedure coupled with Importance Performance Map Analysis (Sabbir et al., 2020; Yuan et al., 2024).

Despite digital agricultures' expansion, farmers' intentions to adopt digital input-purchasing platforms in Natural Farming remain poorly understood. Adoption research largely emphasises conventional agricultural technologies, overlooking platform-specific behavioural factors. While Natural Farming's environmental, economic, and policy dimensions are documented (Bharucha et al., 2020; Koner & Laha, 2021; Kumar et al., 2023; Saride & Sharad, 2024; Shanmuka et al., 2025), evidence on digital platform adoption, remains scarce. This study therefore extends UTAUT to identify behavioural factors influencing Natural Farming farmers' intentions to adopt a digital input-purchasing platform in Andhra Pradesh. Seven hypotheses are examined: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions and Personal Innovativeness positively influence behavioural intention, whereas Perceived Risk and Perceived Cost are expected to act negatively upon it.

METHODOLOGY

To ensure adequate representation of Natural Farming farmers, multi-stage stratified random sampling was used. In each district,

the agricultural division with the largest area under the Andhra Pradesh Community-Managed Natural Farming programme was selected first. Gram Panchayats, each with at least 50 registered Natural Farming farmers, were then randomly chosen from every selected division. Finally, farmers were randomly drawn from village-level *Rythu Sadhikara Samstha* registers, stratified by length of Natural Farming experience (under four years versus four years or longer). Across 17 districts, the largest-APCNF-area division in each was selected (17 divisions, 440 gram panchayats); of 810 farmers approached, 15 were excluded for incomplete or invalid responses, retaining 795. Because the division with largest APCNF area was chosen per district, the sample favours areas of more established Natural Farming activity, under-representing those with fewer farmers.

An a priori sample size calculation was conducted using G*Power 3.1.9.7. The analysis was specified under F-test family, using linear multiple regression with seven predictors, an alpha level of 0.05, statistical power of 0.80, and a medium effect size of f squared equal to 0.15 (Yang et al., 2024). These parameters indicated a minimum required sample size of 103 participants.

Data collection ran from July to November 2024 using a structured questionnaire. Its first section outlined a hypothetical, generic digital platform for procuring Natural Farming inputs; the platform let farmers browse and select ready-made inputs, view product and price details, order, pay, arrange delivery and tracking, and access information in Telugu. The Second section gathered respondents' demographic and farm-level details; and a third measured 27 reflective indicators corresponding to seven constructs and to behavioural intention, each assessed on a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). Every indicator was adapted from previously validated instruments (Venkatesh et al., 2003; Luarn & Lin, 2005; Venkatesh et al., 2012; Ahn et al., 2016; Hu et al., 2019). The questionnaire was translated into Telugu and back into English, and refined through a pilot exercise involving 20 farmers who were not included in the final dataset.

Prior to multivariate analysis, a series of preconditions were verified (Leong et al., 2020). As all constructs were self-reported at one time, common method bias was assessed using Harman's single-factor test, which returned 26.1% (below 50%) and full-collinearity VIFs (1.013–2.024) stayed below 3, indicating minimal distortion. The Shapiro–Wilk test indicated that data departed from normality (Chin et al., 2015); the scatter of residuals pointed to homoscedasticity; and Variance Inflation Factors, all below three, indicated an absence of multicollinearity (Hew & Kadir, 2016). The Artificial Neural Network was therefore paired with SEM to capture any non-linear and non-compensatory relationships and to rank predictors, rather than on basis of normality result (Lee et al., 2022).

The analytical workflow unfolded across three phases. First, Partial Least Squares Structural Equation Modelling in SmartPLS 4 assessed indicator reliability, internal consistency, convergent and discriminant validity and path coefficients, drawing on 5,000 bootstrap resamples. In second phase, a multi-layer perceptron ANN was estimated in IBM SPSS, taking all seven predictors as inputs and behavioural intention as output. The network comprised one hidden layer of four neurons, with a sigmoid activation function in hidden and output layers, the input variables were standardised,

and network was trained using the gradient-descent algorithm. In third phase, Importance Performance Map Analysis in SmartPLS 4 transformed total effects into importance and performance values on a 0-to-100 scale.

RESULTS

The 795 participants were predominantly aged 30 to 39 years (40.88%) and male (65.79%). With respect to education, 35.22% had attained a degree or a higher credential. Marginal and small farmers holding less than three acres made up 87.30% of sample, mirroring wider composition of agriculture in Andhra Pradesh, and a majority reported four to eight years of experience with Natural Farming (56.86%).

Measurement model assessment

Determination of the reflective measurement model began with indicator reliability (Table 1), which captures how much of an items' variance is attributable to its underlying construct (Hair et al., 2019); loading greater than 0.708 is acceptable, the point at which a construct explains over 50% of an indicators' variance (Hair et al., 2021). The second step concerns internal consistency reliability, which measures how strongly indicators of the same construct correlate with each other (Hair et al., 2021). Output from the PLS algorithm confirmed robust construct reliability across the model, as every Cronbachs' alpha and composite reliability

coefficient surpassed 0.70 (Leong et al., 2020). Finally, convergent validity was assessed with average variance extracted (AVE), reflecting how well a construct explains its indicators' variance (Hair et al., 2021). AVE values above 0.50 confirmed satisfactory convergence, establishing construct validity (Fornell & Larcker, 1981).

Discriminant validity is the fourth step; it captures how far one construct is empirically separable from the others within the structural model (Hair et al., 2021). As shown in Table 2, each Heterotrait–Monotrait (HTMT) ratio lies beneath the 0.90 threshold (Henseler et al., 2015; Hair et al., 2021), confirming that the model satisfied discriminant validity.

Discriminant validity used bootstrapped 95% CIs from 5,000 subsamples. Under the HTMT inference criterion (Henseler et al., 2015), no interval included 1, so each construct pair is empirically distinct. The ratios linking Personal Innovativeness with Effort Expectancy and Behavioural Intention are relatively high as innovative farmers find such tools easier, but their value still exclude 1, so discriminant validity holds.

Structural model and hypothesis testing

With every predictor returning a Variance Inflation Factor under three, multicollinearity was ruled out. Table 3 sets out the structural path coefficients. Behavioural intention was significantly and positively shaped by Personal Innovativeness ($\beta = 0.483$, $p < 0.001$),

Table 1. Reliability, validity and outer loadings of constructs

Construct	Cronbach α	CR	AVE	Items	Outer loadings
Behavioural Intention	0.87	0.91	0.72	BI1–BI4	0.78, 0.81, 0.87, 0.91
Effort Expectancy	0.89	0.93	0.82	EE1–EE3	0.91, 0.93, 0.86
Facilitating Conditions	0.81	0.87	0.63	FC1–FC4	0.76, 0.72, 0.82, 0.85
Perceived Cost	0.82	0.88	0.71	PC1–PC3	0.86, 0.79, 0.87
Performance Expectancy	0.88	0.92	0.73	PE1–PE4	0.86, 0.88, 0.78, 0.88
Personal Innovativeness	0.73	0.88	0.79	PI1–PI2	0.92, 0.85
Perceived Risk	0.81	0.88	0.71	PR1–PR3	0.89, 0.83, 0.80
Social Influence	0.85	0.89	0.67	SI1–SI4	0.79, 0.74, 0.88, 0.85

CR = composite reliability; AVE = average variance extracted.

Table 2. Heterotrait–Monotrait ratio of correlations

	BI	EE	FC	PC	PE	PI	PR
EE	0.61 (0.54, 0.68)						
FC	0.48 (0.40, 0.56)	0.50 (0.43, 0.57)					
PC	0.37 (0.28, 0.46)	0.33 (0.25, 0.42)	0.18 (0.10, 0.27)				
PE	0.51 (0.43, 0.59)	0.43 (0.35, 0.52)	0.22 (0.14, 0.30)	0.71 (0.63, 0.77)			
PI	0.83 (0.77, 0.88)	0.84 (0.77, 0.91)	0.58 (0.49, 0.66)	0.34 (0.24, 0.44)	0.51 (0.42, 0.60)		
PR	0.13 (0.06, 0.23)	0.30 (0.21, 0.39)	0.10 (0.06, 0.18)	0.10 (0.05, 0.18)	0.13 (0.06, 0.22)	0.23 (0.12, 0.32)	
SI	0.04 (0.03, 0.11)	0.03 (0.02, 0.11)	0.04 (0.04, 0.10)	0.10 (0.05, 0.19)	0.04 (0.03, 0.12)	0.04 (0.03, 0.13)	0.04 (0.03, 0.10)

BI = Behavioural Intention; EE = Effort Expectancy; FC = Facilitating Conditions; PC = Perceived Cost; PE = Performance Expectancy; PI = Personal Innovativeness; PR = Perceived Risk; SI = Social Influence.

Table 3. Structural path coefficients and hypothesis testing results

Hypothesis	Path	β	95% CI (bootstrap)	f ²	p value	Result
H1	PE $\rightarrow$ BI	0.165	[0.090, 0.244]	0.028	<0.001	Significant
H2	EE $\rightarrow$ BI	0.100	[0.015, 0.183]	0.010	0.020	Significant
H3	SI $\rightarrow$ BI	0.021	[-0.051, 0.081]	0.001	0.549	Not Significant
H4	FC $\rightarrow$ BI	0.120	[0.055, 0.188]	0.023	<0.001	Significant
H5	PI $\rightarrow$ BI	0.483	[0.400, 0.566]	0.240	<0.001	Significant
H6	PR $\rightarrow$ BI	-0.024	[-0.069, 0.029]	0.001	0.331	Not Significant
H7	PC $\rightarrow$ BI	0.040	[-0.021, 0.104]	0.002	0.211	Not Significant

Table 4. Artificial Neural Network sensitivity analysis and IPMA

Predictor	Mean importance	Normalised (%)	IPMA Importance	IPMA Performance
Personal Innovativeness	0.39	100	0.472	69.2
Performance Expectancy	0.18	47	0.222	74.8
Effort Expectancy	0.14	36	0.092	65.4
Facilitating Conditions	0.12	30	0.125	65.1
Perceived Cost	0.09	24	0.05	75.6
Perceived Risk	0.04	11	-0.021	54.1
Social Influence	0.03	7	0.024	70.3

Performance Expectancy ($\beta = 0.165$, $p < 0.001$), Facilitating Conditions ($\beta = 0.120$, $p < 0.001$) and Effort Expectancy ($\beta = 0.100$, $p < 0.05$), which lent support to hypotheses H1, H2, H4 and H5. By contrast, Social Influence ($\beta = 0.021$, $p > 0.05$), Perceived Risk ($\beta = -0.024$, $p > 0.05$) and Perceived Cost ($\beta = 0.040$, $p > 0.05$) were insignificant, so hypotheses H3, H6 and H7 were rejected. Overall, the structural model explained 51.8% of variance in behavioural intention ($R^2 = 0.518$). Predictive relevance was assessed with the PLSpredict procedure (Shmueli et al., 2019), using ten-fold cross-validation with ten repetitions. All four behavioural intention indicators returned positive Q^2 predict values (BI-1: 0.39, BI-2: 0.24, BI-3: 0.43 and BI-4: 0.36), confirming the model's predictive relevance.

Artificial Neural Network and importance-performance analysis

Averaged over the ten-fold cross-validation, the Root Mean Square Error was 0.102 during training and 0.094 during testing, signalling that the network generalized effectively without overfitting and normalized importance from sensitivity analysis (Table 4). A subsequent Importance Performance Map Analysis, run in SmartPLS 4, appraised the importance and performance of all seven

constructs simultaneously (Alhumaid et al., 2021). This analysis placed Personal Innovativeness foremost in importance, trailed by Performance Expectancy, Facilitating Conditions, Effort Expectancy, Perceived Cost, Social Influence and Perceived Risk. A side-by-side comparison of importance rankings yielded by PLS-SEM, Artificial Neural Network and Importance Performance Map Analysis techniques is presented in Table 5.

DISCUSSION

The results identify Personal Innovativeness as the foremost factor behind the intention to adopt digital platforms among Natural Farming farmers in Andhra Pradesh, echoing Alharbi and Sohaib (2021); Sonu and Jha (2025); Singh et al. (2026). Farmers are more inclined to use digital platforms when they believe these technologies are beneficial and capable of producing intended results. The pattern is consistent with Mangudhla et al. (2026), which identifies individual adaptive capacity as a principal force shaping adaptation behaviour. This underscores the need for responsive extension practices that help farmers adopt digital technologies.

Performance Expectancy has a significant and positive association with behavioural intention, aligning with Cimino et al. (2024). Natural Farming farmers show greater willingness to adopt digital platforms when they perceive these tools as useful for achieving desired outcomes. A comparable significant and positive effect was observed for Effort Expectancy, supporting Shi et al. (2022); platforms perceived as straightforward and easy to operate are more readily adopted. These findings favour practical demonstrations, farmer training and user-friendly interfaces. Social Influence was insignificant (Li et al., 2024), so adoption depends less on social validation than on direct utility.

Facilitating Conditions has a positive and significant effect on behavioural intention, implying that technology-enabling services, including digital payment facilities, capable platforms and wider internet access, are instrumental in motivating Natural Farming farmers to embrace digital platforms, corroborating Jain et al. (2025).

Table 5. Convergent importance rankings across three methods

Construct	IPMA	PLS-SEM	ANN
Personal Innovativeness	1	1	1
Performance Expectancy	2	2	2
Facilitating Conditions	3	3	4
Effort Expectancy	4	4	3
Perceived Cost	5	5	5
Social Influence	6	7	7
Perceived Risk	7	6	6

IPMA = Importance Performance Map Analysis; PLS-SEM = Partial Least Squares Structural Equation Modelling; ANN = Artificial Neural Network.

Extension systems must therefore provide connectivity, advisory support and institutional assistance, and strengthen digital literacy to turn access into sustained platform use.

Perceived Cost does not significantly affect behavioural intention. This suggests that perceived financial barriers may be less influential when farmers recognise the benefits of digital platforms and that perceived value can outweigh associated costs. This underscores the need to communicate the broader value of digital technologies. Wang et al. (2026), reported that the adoption of digital technology by Chinese farmers responds more to access and complementary services than to direct expense. Perceived Risk is similarly non-significant, in agreement with Zeng et al. (2016), reflecting the possibility that progress in digital technology has made associated risks more manageable as users become more knowledgeable and better prepared to handle them.

Though non-significant in the SEM, Perceived Cost retained a moderate normalised importance (24%) in the ANN, suggesting a non-linear influence a linear model would not capture (Lee et al., 2022; Yuan et al., 2024; Soomro et al., 2025; Yu et al., 2026; Pragnya et al., 2026). One plausible interpretation is that cost becomes salient only at levels higher than those experienced by most respondents in this sample; however, present analysis did not directly test for such a threshold, this reading remains suggestive rather than confirmed. With small and marginal farmers at 87.30% of the sample, the chief drivers appear to be farmer disposition and infrastructure rather than cost affordability.

Taken together, PLS-SEM, ANN and IPMA indicate that Personal Innovativeness is crucial in influencing the behavioural intention of farmers to embrace digital platforms, consistent with Alharbi and Sohaib (2021). Farmers inclined to experiment with new digital technologies are more likely to recognise their advantages, reinforcing the need for farmer-centred training, advisory support, digital literacy and enabling institutional conditions.

CONCLUSION

This research demonstrates that, among the factors shaping Natural Farming farmers' intention to adopt digital platforms for sourcing Natural Farming inputs, Personal Innovativeness ranks as the most influential, followed by Performance Expectancy, Effort Expectancy and Facilitating Conditions. Enriched by the addition of Personal Innovativeness, Perceived Cost and Perceived Risk, extended framework shows considerable explanatory strength in accounting behaviour intentions towards digital platforms among smallholder Natural Farming communities. The practical implications are spending on rural digital infrastructure, provision of affordable internet connectivity and design of incentive-based policy instruments should be treated as essential foundations for digital transitions in agriculture. To strengthen farmers' behavioural intention in a way that is both substantive and inclusive, technology developers and venture initiators need to build platforms that are responsive to innovative perspectives and resource constraints of Natural Farming practitioners.

DECLARATIONS

Ethics approval and consent of participation: The research advisory committee of Rajendra Mishra School of Engineering

Entrepreneurship, Indian Institute of Technology, Kharagpur, West Bengal, India waived the ethical approval. Participation was voluntary, and verbal informed consent was obtained from all respondents. The confidentiality and anonymity of participants were strictly maintained throughout the research process.

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

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