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Adoption of Agri-Tech and Precision Farming Among Entrepreneurs in Dakshina Kannada: An Extended TAM Approach

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***Abstract* - Improving productivity and sustainability in agriculture depends on understanding the factors influencing technology adoption. The Technology Acceptance Model (TAM), particularly its core constructs-Attitude Toward Use (ATU), Perceived Ease of Use (PEOU), and Perceived Usefulness (PU)-has been widely used to explain user adoption behavior. However, few studies, particularly in rural and agri-tech contexts, have integrated contextual factors such as farm size, technological awareness, and gender into this framework. This study aims to examine how ATU, PEOU, and PU influence Behavioral Intention (BI) to adopt agricultural technology. It also seeks to determine whether BI is affected by contextual and demographic factors, including farm size, technological knowledge, and gender. A structured survey was conducted among 120 agricultural respondents. Structural equation modeling (SEM) was used to test the interrelationships among TAM constructs. Independent samples t-tests and one-way ANOVA were employed to examine group-based differences in BI with respect to gender, farm size, and technological awareness. PU emerged as the strongest predictor of BI, while ATU was also a significant positive influence. PEOU contributed indirectly by enhancing both ATU and PU. ATU partially mediated the relationship between PU and BI. Although gender differences were not statistically significant, BI varied significantly across groups based on farm size and technological knowledge. The findings highlight the importance of incorporating contextual variables and reaffirm the robustness of TAM in explaining agri-tech adoption. Tailored strategies that enhance technological awareness and demonstrate clear benefits to diverse user groups can improve adoption rates. These insights are valuable for policymakers, technology developers, and educators seeking to bridge gaps in the diffusion of agricultural technologies.**
***Keywords:* Technology Acceptance Model (TAM), Agricultural Technology Adoption, Behavioral Intention (BI), Perceived Usefulness (PU), Technological Awareness**

I. INTRODUCTION

In Dakshina Kannada, where agriculture supports many micro-entrepreneurs, the acceptance of agri-tech and precision farming is essential for improving agricultural productivity and sustainability. Precision farming enhances site-specific management, resource optimization, and crop management through the use of technologies such as GPS, GIS, remote sensing, and data analytics (Gawande *et al.,* 2023; Masi *et al.,* 2022). Despite advantages such as increased yields and cost savings (Sangeetha *et al.,* 2023), adoption remains uneven due to various barriers. Broader adoption among agricultural entrepreneurs in Dakshina Kannada requires a systematic approach. This study applies the Extended Technology Acceptance Model (TAM) to evaluate the factors influencing the acceptance of agri-tech and precision farming.

While the traditional TAM emphasizes perceived usefulness (PU) and perceived ease of use (PEOU) as primary determinants of adoption (Jiménez *et al.,* 2020), the extended model incorporates attitude toward use (ATU) as a mediating factor, along with demographic and business variables to analyze variations in adoption behavior. This study offers insights into how various entrepreneurial groups in Dakshina Kannada perceive and implement agri-tech innovations. It addresses the following research questions:

1. How does behavioral intention (BI) to adopt agri-tech and precision farming vary with perceived usefulness and perceived ease of use?
2. In what way does attitude toward use (ATU) serve as a mediator?
3. How do demographic and business-related factors influence adoption trends?

By exploring these questions, the study identifies key enablers and barriers to agri-tech adoption, offering valuable insights for agricultural institutions, technology developers, and policymakers aiming to design targeted interventions that enhance adoption rates.

It also extends the application of TAM within agriculture, underscoring its relevance for understanding entrepreneurial behavior in precision farming (Bilali *et al.,* 2021). The findings will support the development of policies that promote sustainable agricultural practices in Dakshina Kannada, ensuring the effective integration of new technologies into the region's farming systems.

II. RESEARCH OBJECTIVES

1. To examine the key factors influencing the adoption of agri-tech and precision farming among entrepreneurs in Dakshina Kannada.
2. Toanalyze differences in agri-tech and precision farming adoption across various demographic and business-related groups.
3. To investigate the mediating role of attitude toward use in the relationship between perceived usefulness and behavioral intention to use (BIU) agri-tech and precision farming.
4. To provide recommendations for policymakers, technology providers, and agricultural institutions to facilitate the adoption of agri-tech and precision farming.

III. REVIEW OF LITERATURE

Extensive application of the Technology Acceptance Model (TAM) and its variants has helped clarify the dynamics of technology adoption across various fields. Core constructs-perceived usefulness (PU), perceived ease of use (PEOU), attitude toward use (ATU), and behavioral intention (BI)-are consistently cited as major predictors of user adoption behavior. In their analysis of DigiLocker adoption in Mangaluru, Raghavendra and Shruthi (2025) found that PU and PEOU notably influenced BI, with ATU mediating this link. Similarly, Raghavendra and Aparna (2024) observed that PU was the primary driver of hawkers' adoption of the Unified Payments Interface (UPI), while PEOU had an indirect effect through ATU.

These results align with Mortimer *et al.,* (2020), who emphasized the influence of trust and innovation on mobile banking attitudes. In an agricultural context, Chatterjee *et al.,* (2021) demonstrated that PU influences PEOU, which in turn impacts both ATU and BI. Wang *et al.,* (2022) further validated the mediating role of ATU in the PU-BI relationship among farmers adopting digital farming technologies.

In digital learning environments, Raghavendra and Shruthi N. (2025) reported similar trends, where PU and PEOU significantly affected teachers' adoption of e-learning tools. Teo (2021) confirmed these findings, highlighting the dominant role of these constructs in shaping attitudes and intentions toward e-learning. Earlier, Chen *et al.,* (2002) found that while PU directly affects BI, PEOU influences it indirectly via ATU, reinforcing the mediating role of ATU in TAM. Expanding TAM through UTAUT2, Venkatesh *et al.,* (2021) investigated technology adoption in small businesses and identified PU, ATU, and BI as key determinants. This was echoed in digital banking research by Gefen *et al.,* (2023), who confirmed that PU and ATU mediate the relationship between system reliability and BI. Supporting this view, Vidyapriya and Mohanasundari (2015) found that rural consumers in South India adopted banking technologies based on their perceptions of usefulness and ease of use. Similarly, Mwita (2019) reported that self-employment intentions among Tanzanian students were significantly influenced by PU and PEOU, underscoring how favorable perceptions of technology can inspire entrepreneurial behavior. Recent studies have also extended TAM applications to sustainability, service evaluation, and post-pandemic digital adaptation. For example, Raghavendra and Diddimani (2025), examining green consumer behavior, highlighted how contextual and psychological factors-including perceptions of technological convenience-shape environmentally responsible technology use.

In the transport sector, Keertana and Vishnukumar (2024) showed that demographic differences significantly influence customer satisfaction with digital bus services in Chennai, which are largely driven by perceived convenience and usefulness. During the COVID-19 lockdown, Parvin (2022) found that female college students in Bangladesh increasingly relied on online food delivery apps, driven by perceived ease and utility. In a study of occupational stress in West Bengal, Gupta (2020) suggested that digital solutions-if perceived as easy and helpful-could reduce workplace stress, indicating the broader applicability of TAM beyond traditional settings. Taken together, these findings support the robustness and adaptability of TAM across various domains, including digital platforms, fintech, e-learning, agriculture, rural banking, green consumption, transportation, and health-related work environments. The consistent relevance of PU, PEOU, ATU, and BI confirms their universal applicability in understanding and predicting technology adoption behavior.

IV. THEORETICAL FOUNDATION AND RESEARCH HYPOTHESES

A. Theoretical Foundation

Grounded in the extended Technology Acceptance Model (TAM), this study provides a framework for understanding the adoption of agri-tech and precision farming among entrepreneurs in Dakshina Kannada. Originally developed by Davis (1989), TAM explains technology adoption using two key constructs: perceived usefulness (PU)-the degree to which a user believes a technology will enhance performance-and perceived ease of use (PEOU)-the degree to which a technology is considered easy to use. These constructs influence attitude toward use (ATU), thereby affecting behavioral intention (BI) and actual adoption behavior.

This paper extends TAM by incorporating ATU as a mediating variable and considering demographic and business-related factors as grouping variables, enabling a more nuanced understanding of agri-tech adoption across different entrepreneurial sectors. Previous research (Venkatesh &Bala, 2008; Jiménez *et al.,* 2020) has emphasized the critical role of attitudes in translating perceptions into behavioral intentions. Since precision farming in agriculture requires behavioral adaptation, TAM is especially relevant for the decision-making processes of microentrepreneurs. This study empirically tests the interrelationships among PU, PEOU, ATU, and BI using structural equation modeling (SEM), thereby offering insights into the drivers and barriers of agri-tech adoption in Dakshina Kannada.

B. Research Hypotheses

Based on the extended Technology Acceptance Model (TAM) and prior literature, this study formulates the following hypotheses to examine the factors influencing the adoption of agri-tech and precision farming among entrepreneurs in Dakshina Kannada:

1. *H1*: Perceived ease of use (PEOU) has a significant positive effect on perceived usefulness (PU).
2. *H2:* Perceived ease of use (PEOU) has a significant positive effect on attitude toward use (ATU).
3. *H3:* Perceived usefulness (PU) has a significant positive effect on attitude toward use (ATU).
4. *H4:* Perceived usefulness (PU) has a significant positive effect on behavioral intention (BI).
5. *H5:* Attitude toward use (ATU) has a significant positive effect on behavioral intention (BI).
6. *H6:* Attitude toward use (ATU) mediates the relationship between perceived usefulness (PU) and behavioral intention (BI).

To assess the impact of key demographic and business-related factors on behavioral intention (BI), the study further hypothesizes:

7. *H7*: There is a significant difference in behavioral intention (BI) based on gender.
8. *H8*: There is a significant difference in behavioral intention (BI) based on farm size.
9. *H9:* There is a significant difference in behavioral intention (BI) based on technological awareness.

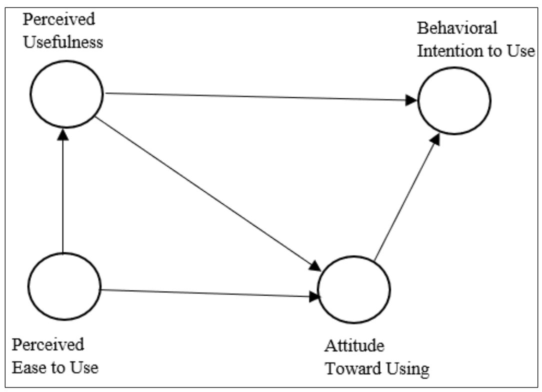

Fig.1 Conceptual Model

V. RESEARCH METHODOLOGY

This study uses the extended Technology Acceptance Model (TAM) to investigate the factors influencing the acceptance of agri-tech and precision farming among entrepreneurs in Dakshina Kannada, employing a quantitative research methodology. Primary data were collected through a structured questionnaire survey, and a literature review positioned the results within the context of existing research. Using disproportionate stratified random sampling, the target population consisted of entrepreneurs engaged in agriculture and precision farming across the nine taluks of Dakshina Kannada. The final sample included 122 respondents. The questionnaire was based on validated scales and focused on TAM constructs: Attitude Toward Use (ATU), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioral Intention (BI)**.** Demographic and business-related variables were also included. Secondary data collection involved a literature review using sources such as Google Scholar and Semantic Scholar. Data were analyzed using SmartPLS**,** focusing on the relationships among the extended TAM constructs. Descriptive statistics summarized the characteristics of the respondents, and validity and reliability testing ensured robust measurement scales. Structural equation modeling (SEM) was used to test the hypotheses regarding the influence of PU, PEOU, and ATU on BI. Independent samples t-tests and one-way ANOVA were employed to examine adoption patterns across demographic and business-related groupings. In adherence to ethical research standards, informed consent was obtained, and confidentiality and anonymity of all respondents were maintained.

VI. RESULTS

The distribution of respondents by demographic and contextual factors shows that the majority were male (83.61%), while female respondents accounted for 16.39%. The largest age group was under 30 years (31.15%), followed by those aged 30-40 years (29.51%), 41-50 years (24.59%), and over 50 years (14.75%). In terms of farm size, small-scale farmers (owning less than two acres) comprised 50.82% of the sample; medium-scale and large-scale farmers accounted for 29.51% and 19.67%, respectively. Regarding technological awareness, only 9.84% of respondents were highly aware; the majority were moderately aware (50.82%), followed by slightly aware individuals (39.34%). No respondent reported being completely unaware. The standard deviation values were all below 1, indicating low variability in responses. The mean values for all indicators ranged between 4.60 and 5.91, reflecting moderate to high levels of agreement. An assessment of normality showed that kurtosis values fell within ±7 and skewness values within ±2, indicating no significant deviations from normality. These findings confirm that the data distribution was appropriate for subsequent statistical analyses.

TABLE I DISTRIBUTION OF RESPONDENTS BY DEMOGRAPHIC AND CONTEXTUAL FACTORS

Category	Option	Frequency	Percentage (%)
Gender	Male	102	83.61
	Female	20	16.39
	Other	0	0.00
	Total	122	100.00
Age Group	Below 30 years	38	31.15
	30-40 years	36	29.51
	41-50 years	30	24.59
	Above 50 years	18	14.75
	Total	122	100.00
Farm Size	Small-scale (Less than 2 acres)	62	50.82
	Medium-scale (2-5 acres)	36	29.51
	Large-scale (More than 5 acres)	24	19.67
	Total	122	100.00
Technology Awareness	Not aware at all	0	0.00
	Slightly aware	48	39.34
	Moderately aware	62	50.82
	Highly aware	12	9.84
	Total	122	100.00

Source: Author's work

TABLE II DESCRIPTIVE STATISTICS OF CONSTRUCTS AND INDICATORS

Construct	Indicator	Mean	Standard Deviation	Skewness	Kurtosis
PU (Perceived Usefulness)	USEF1	5.06	0.88	0.70	2.39
	USEF2	4.73	0.56	-1.33	4.80
	USEF3	5.40	0.78	-1.44	5.73
	USEF4	5.75	0.58	-0.95	-1.35
	USEF5	4.96	0.71	-0.20	-0.38
PEOU (Perceived Ease of Use)	EOU1	5.42	0.56	-0.62	0.30
	EOU2	5.18	0.81	-0.90	1.63
	EOU3	5.39	0.52	0.32	-1.47
	EOU4	4.60	0.88	1.40	4.28
	EOU5	4.96	0.54	0.55	0.96
ATU (Attitude Toward Use)	ATT1	4.68	0.70	-1.40	5.18
	ATT2	4.89	0.77	-0.56	1.68
	ATT3	5.32	0.57	1.41	3.98
	ATT4	5.91	0.86	0.29	5.30
	ATT5	4.63	0.58	-1.36	-0.07
BI (Behavioral Intention)	BI1	5.08	0.61	0.99	0.21
	BI2	4.92	0.72	-1.08	4.22
	BI3	4.61	0.89	0.82	-1.21

Source: Author's work

TABLE III INDEPENDENT SAMPLES TEST

Levene's Test for Equality of Variances	t-test for Equality of Means
F	**Sig.**
0.524	0.470
* Significant at p < 0.05	0

Source: Author's work

An independent samples *t*-test was conducted to compare behavioral intention (BI) between male and female respondents. Levene's test for equality of variances was not significant, F (1, 120) = 0.525, p = .470, indicating that the assumption of homogeneity of variances was met. The results showed no statistically significant difference in BI between male and female respondents.

TABLE IV ANOVA FOR FARM SIZE AND BI

Source of Variation	Sum of Squares	df	Mean Square	F	Sig. (p-value)
Between Groups	2.732	2	1.366	3.229	0.0431*
Within Groups	50.733	119	0.426	0	0
Total	53.465	121	0	0	0
* Significant at **p < 0.05**					

Source: Author's work

A one-way ANOVA was conducted to examine behavioral intention (BI) in relation to farm size. The analysis revealed a statistically significant variation among the farm size categories, F (2, 119) = 3.23, p = .043. These results indicate that BI is significantly influenced by farm size.

TABLE V ANOVA FOR TECHNOLOGY AWARENESS AND BI

Source of Variation	Sum of Squares	df	Mean Square	F	Sig. (p-value)
Between Groups	3.858	2	1.929	4.231	0.0168*
Within Groups	54.273	119	0.456	0	0
Total	58.131	121	0	0	0
* Significant at p < 0.05					

Source: Author's work

The influence of technological awareness on behavioral intention (BI) was investigated using a one-way ANOVA. The results revealed a statistically significant effect, F(2, 119) = 4.23, p = .017, indicating that BI is significantly influenced by technological awareness.

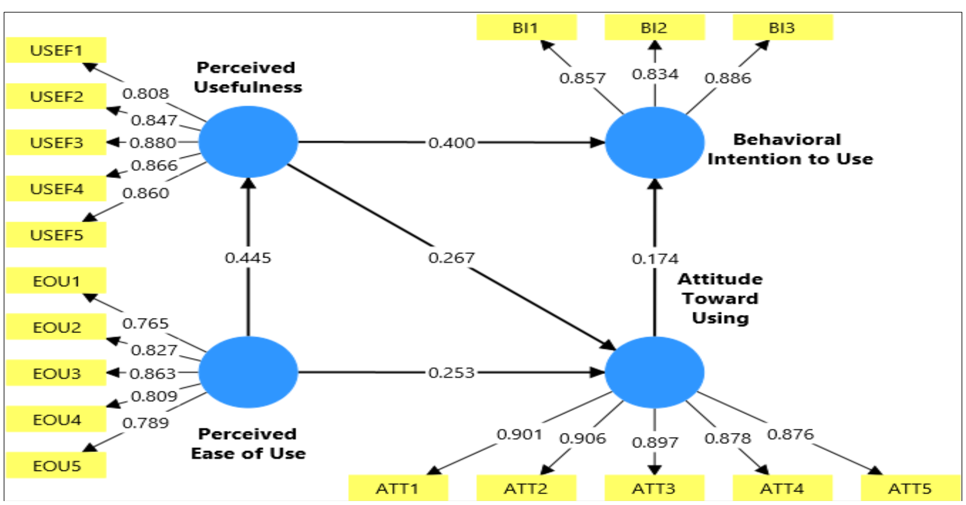

Fig. 2 Path Analysis Model

For the proposed model, model fit was assessed using the standardized root mean square residual (SRMR) and the Normed Fit Index (NFI). Indicating a reasonable model fit, the SRMR value of 0.078 fell within the acceptable range (≤ 0.08). Although slightly below the recommended cut-off of 0.90, the NFI value of 0.888 suggests a reasonably good fit. These findings indicate that the structural model fit the data generally satisfactorily.

TABLE VI MEASUREMENT MODEL ASSESSMENT - RELIABILITY AND CONVERGENT VALIDITY

Construct	Indicator	Outer Loading	Cronbach's Alpha (α)	Composite Reliability (CR)	AVE
PU (Perceived Usefulness)	USEF1	0.808	0.906	0.906	0.727
	USEF2	0.847	0	0	0
	USEF3	0.880	0	0	0
	USEF4	0.866	0	0	0
	USEF5	0.860	0	0	0
PEOU (Perceived Ease of Use)	EOU1	0.765	0.870	0.875	0.658
	EOU2	0.827	0	0	0
	EOU3	0.863	0	0	0
	EOU4	0.809	0	0	0
	EOU5	0.789	0		0
ATU (Attitude Toward Use)	ATT1	0.901	0.936	0.940	0.796
	ATT2	0.906	0	0	0
	ATT3	0.897	0	0	0
	ATT4	0.878	0	0	0
	ATT5	0.876	0	0	0
BI (Behavioral Intention)	BI1	0.857	0.825	0.844	0.738
	BI2	0.834	0	0	0
	BI3	0.886	0	0	0

Source: Author's work

The measurement model assessment verified reliability and convergent validity using Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE). All indicators met the required criteria: outer loadings exceeded 0.70, ensuring item reliability (Hair *et al.,* 2019). CR values were above the 0.70 threshold, confirming construct reliability, and Cronbach's alpha values also exceeded 0.70, indicating internal consistency (Nunnally & Bernstein, 1994). AVE values were above 0.50, supporting adequate convergent validity-indicating that each construct explains at least 50% of the variance in its indicators (Fornell&Larcker, 1981).

TABLE VII DISCRIMINANT VALIDITY - HETEROTRAIT-MONOTRAIT (HTMT) RATIO

	ATU	BI	PEOU	PU
ATU	0	0	0	0
BI	0.362	0	0	0
PEOU	0.409	0.647	0	0
PU	0.412	0.526	0.500	0

Source: Author's work

Discriminant validity was evaluated using the Heterotrait-Monotrait (HTMT) ratio and the Fornell-Larcker criterion. The HTMT values were below the conservative threshold of 0.85, confirming adequate discriminant validity (Henseler *et al.,* 2015).

TABLE VIII DISCRIMINANT VALIDITY - HETEROTRAIT-MONOTRAIT (HTMT) RATIO

	ATU	BI	PEOU	PU
ATU	0.892	0	0	0
BI	0.326	0.859	0	0
PEOU	0.372	0.552	0.811	0
PU	0.380	0.466	0.445	0.853

Source: Author's work

The Fornell-Larcker criterion further supports discriminant validity, as the square root of the AVE for each construct is greater than its correlation with any other construct (Fornell&Larcker, 1981).

TABLE IX COLLINEARITY STATISTICS (VARIANCE INFLATION FACTOR - VIF)

	VIF
ATT1	3.641
ATT2	3.901
ATT3	3.356
ATT4	3.834
ATT5	3.866
BI1	1.646
BI2	2.020
BI3	2.171
EOU1	1.748
EOU2	2.062
EOU3	2.419
EOU4	1.958
EOU5	1.871
USEF1	2.005
USEF2	2.407
USEF3	2.898
USEF4	2.740
USEF5	2.525

Source: Author's work

Collinearity statistics, assessed using the variance inflation factor (VIF), indicated that all values were below the threshold of 5, suggesting no serious multicollinearity issues (Hair *et al.,* 2019). With strong reliability, convergent validity, discriminant validity, and no multicollinearity concerns, the measurement model demonstrated an acceptable overall fit, supporting the robustness of the constructs used in the study.

TABLE X HYPOTHESES TEST SUMMARY

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T-Statistics	P-Values	Decision
ATU → BI	0.174	0.175	0.034	5.149	0.000	Accept
PEOU → ATU	0.253	0.254	0.036	7.073	0.000	Accept
PEOU → PU	0.445	0.447	0.037	12.104	0.000	Accept
PU → ATU	0.267	0.267	0.036	7.504	0.000	Accept
PU → BI	0.400	0.400	0.039	10.342	0.000	Accept
PU → ATU → BI	0.046	0.047	0.010	4.530	0.000	Accept

Source: Author's work

Attitude toward use (ATU) significantly affected behavioral intention (BI), $\beta = 0.174$, $t = 5.149$, $p < .001$, according to the results of hypothesis testing. ATU ($\beta = 0.253$, $t = 7.073$, $p < .001$) and perceived usefulness (PU) ($\beta = 0.445$, $t = 12.093$, $p < .001$) were significantly influenced by perceived ease of use (PEOU). Additionally, ATU ($\beta = 0.267$, $t = 7.504$, $p < .001$) and BI ($\beta = 0.400$, $t = 10.954$, $p < .001$) were significantly influenced by PU. Furthermore, the mediating effect of ATU on the PU-BI relationship was noteworthy, $\beta = 0.046$, $t = 4.530$, $p < .001$. All relationships were statistically significant ($p < .05$), thereby supporting the proposed hypotheses

TABLE XI HYPOTHESIS TESTING RESULTS OF GROUPING VARIABLES

Hypothesis	Statistical Test	Decision
H7: There is a significant difference in Behavioral Intention (BI) based on Gender.	Independent Samples t-test	Not Supported
H8: There is a significant difference in the (BI) based on Farm Size.	One-way ANOVA	Supported
H9: There is a significant difference in Behavioral Intention (BI) based on technological Awareness.	One-way ANOVA	Supported

Source: Author's work

The results of hypothesis testing indicate that gender has no significant influence on behavioral intention (H7 not supported). In contrast, behavioral intention shows notable variation based on farm size (H8 supported) and technological awareness (H9 supported), suggesting that individuals with larger farms and higher levels of awareness exhibit stronger adoption intentions. These findings underscore the need for targeted policies to promote agri-tech adoption based on farm size and levels of technological awareness.

VII. DISCUSSION AND CONCLUSION

The results of the study complement previous research on technology acceptance and provide deeper insight into the primary determinants of behavioral intention (BI). Attitude toward use (ATU) has a significant influence on BI (β = 0.174, p< .001), indicating that individuals with positive attitudes are more likely to adopt technology, thus supporting earlier studies on DigiLocker (Raghavendra & Shruthi, 2025) and digital banking (Gefen *et al.,* 2023). Reinforcing findings from research on AI in agriculture (Chatterjee *et al.,* 2021) and e-learning (Teo, 2021), perceived ease of use (PEOU) significantly affects ATU (β = 0.253, p< .001), underlining that ease of use fosters positive attitudes. Consistent with studies on precision farming (Wang *et al.,* 2022) and fintech (Chen *et al.,* 2002), the strong relationship between PEOU and perceived usefulness (PU) (β = 0.445, p< .001) suggests that users who find technology easy to use also perceive it as more beneficial.

PU also directly influences BI (β = 0.400, p< .001) and has a substantial effect on ATU (β = 0.267, p< .001), underscoring its central role in technology acceptance (Mortimer *et al.,* 2020; Raghavendra & Aparna, 2024; Venkatesh *et al.,* 2021). While PU directly affects BI, its influence is amplified through positive attitudes; hence, the mediating role of ATU in the PU-BI relationship (β = 0.486, p< .001) aligns with the findings of Wang *et al.,* (2022) and Raghavendra and Shruthi (2025).

Variations in adoption behavior based on farm size and technological awareness were identified in the multi-group analysis. The significant effect of farm size on BI (F (2, 119) = 3.229, p = .043) suggests that larger farms may benefit more from adopting technology. Technological awareness also had a substantial impact on BI (F (2, 119) = 4.231, p = .017), indicating that individuals with greater awareness are more likely to embrace technology. However, BI did not vary significantly by gender, suggesting that both male and female users exhibited similar adoption behavior. These findings underscore the importance of designing targeted interventions that account for contextual factors such as farm size and awareness levels to promote successful technology adoption.

A. Theoretical Implications

This study confirms the mediating effect of attitude toward use (ATU) and the differential effects of perceived ease of use (PEOU) and perceived usefulness (PU) across user groups, thereby extending the Technology Acceptance Model (TAM). These findings underscore the importance of incorporating demographic and contextual factors into future adoption models, as well as the global applicability of TAM-based frameworks across diverse settings.

B. Practical Implications

Policymakers, technology providers, and agricultural institutions should emphasize the perceived usefulness (PU) of technology to farmers, ensuring that innovations address their specific needs and support the adoption of Agri-Tech and precision farming. While promoting positive attitudes (ATU) through awareness campaigns and hands-on training, efforts should also focus on enhancing perceived ease of use (PEOU), particularly for small-scale farmers and those with limited technological exposure. Private technology providers should emphasize demonstrating the efficiency and financial benefits of Agri-Tech, whereas public agricultural institutions should prioritize user-friendly solutions and accessibility. Precision farming solutions will be adopted more effectively and sustainably when strategies are tailored to farm size, technological awareness, and user experience.

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Use of Artificial Intelligence (AI)-Assisted Technology for Manuscript Preparation
The authors confirm that no AI-assisted technologies were used in the preparation or writing of the manuscript, and no images were altered using AI.

REFERENCES

[1] Bilali, H., Hassen, T., Bottalico, F., Berjan, S., & Capone, R. (2021). Acceptance and adoption of technologies in agriculture. *Agrofor*, *6*(1), 135–146. https://doi.org/10.7251/agreng2101135e

[2] Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in agriculture: The role of trust, perceived risk, and AI literacy. *Technology in Society*, *67*, 101728. https://doi.org/10.1016/j.techsoc.2021.101728

[3] Chen, L., Gillenson, M., & Sherrell, D. (2002). Enticing online consumers: An extended technology acceptance perspective. *Information and Management*, *39*(8), 705–719. https://doi.org/10.1016/S0378-7206(01)00127-6

[4] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

[5] Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

[6] Gawande, V., Saikanth, D., Sumithra, B., Aravind, S., Swamy, G., Chowdhury, M., & Singh, B. (2023). Potential of precision farming technologies for eco-friendly agriculture. *International Journal of Plant & Soil Science*, *35*(19), 101–112. https://doi.org/10.9734/ijpss/2023/v35i193528

[7] Gefen, D., Karahanna, E., & Straub, D. W. (2023). Trust and TAM in digital banking: An integrated model. *Journal of Information Systems Research*, *35*(1), 58–82.

[8] Gupta, S. K. (2020). Analysis of different factors of occupational stress and associated health problems in West Bengal. *Asian Review of Social Sciences*, *9*(1), 39–47. https://doi.org/10.51983/arss-2020.9.1.1608

[9] Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2019). *A primer on partial least squares structural equation modeling (PLS-SEM)* (2nd ed.). Sage Publications.

[10] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

[11] Jiménez, I., García, L., Violante, M., Marcolin, F., & Vezzetti, E. (2020). Commonly used external TAM variables in e-learning, agriculture, and virtual reality applications. *Future Internet*, *13*(1), 7. https://doi.org/10.3390/fi13010007

[12] Keertana, M., & Vijay Vishnukumar, C. (2024). Exploring the impact of demographics on customer satisfaction with redBus services in Chennai, India. *Asian Review of Social Sciences*, *13*(2), 13–17. https://doi.org/10.70112/arss-2024.13.2.4251

[13] Masi, M., Rosa, M., Vecchio, Y., Bartoli, L., & Adinolfi, F. (2022). The long way to innovation adoption: Insights from precision agriculture. *Agricultural and Food Economics*, *10*(1), 1–14. https://doi.org/10.1186/s40100-022-00236-5

[14] Mortimer, G., Fazal-e-Hasan, S. M., Martin, H., & Grimmer, L. (2020). Explaining mobile banking adoption: The role of trust, innovation characteristics, and attitude. *International Journal of Bank Marketing*, *38*(5), 1096–1116. https://doi.org/10.1108/IJBM-05-2019-0182

[15] Mwita, K. M. (2019). Determinants of self-employment intentions among students in Tanzania higher learning institutions. *Asian Journal of Managerial Science*, *8*(3), 7–14. https://doi.org/10.51983/ajms-2019.8.3.1627

[16] Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

[17] Parvin, N. (2022). Factors influencing online food delivery apps use during COVID-19 lockdown among female college students in Bangladesh. *Asian Review of Social Sciences*, *11*(2), 32–39. https://doi.org/10.51983/arss-2022.11.2.3262

[18] Raghavendra, & Aparna, K. (2024). Factors influencing Unified Payments Interface adoption among hawkers in Mangaluru: An extended Technology Acceptance Model approach. *Asian Journal of Managerial Science*, *13*(2), 45–51. https://doi.org/10.70112/ajms-2024.13.2.4250

[19] Raghavendra, & Diddimani, M. (2025). Determinants of green consumer behavior: Psychological, social, economic, and contextual factors. *Asian Review of Social Sciences*, *14*(1), 1–6. https://doi.org/10.70112/arss-2025.14.1.4286

[20] Raghavendra, & Shruthi, N. (2025). Factors influencing behavioral intention to use DigiLocker among users in Mangaluru City: An extended Technology Acceptance Model approach. *International Journal of Case Studies in Business, IT, and Education*, *9*(1), 1–19. Zenodo. https://doi.org/10.5281/zenodo.14854760

[21] Sangeetha, S., Parameswari, K., & Dhanushkodi, V. (2023). Factors influencing adoption of precision farming technologies in watermelon cultivation. *International Journal of Environment and Climate Change*, *13*(10), 2915–2920. https://doi.org/10.9734/ijecc/2023/v13i102957

[22] Teo, T. (2021). Factors influencing teachers' intention to use technology: Model development and test. *Computers & Education*, *160*, 104034. https://doi.org/10.1016/j.compedu.2020.104034

[23] Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences*, *39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

[24] Venkatesh, V., Thong, J. Y., Xu, X., & Tam, K. Y. (2021). Technology adoption in small businesses: An extended UTAUT2 model. *MIS Quarterly*, *45*(2), 289–317. https://doi.org/10.25300/MISQ/2021/14924

[25] Vidyapriya, P., & Mohanasundari, M. (2015). Customer responsiveness on banking technology products in rural South India. *Asian Journal of Managerial Science*, *4*(1), 27–32. https://doi.org/10.51983/ajms-2015.4.1.1173

[26] Wang, X., Li, L., Zhang, J., & Huang, S. (2022). Factors influencing precision farming adoption: An empirical study. *Computers and Electronics in Agriculture*, *198*, 107035. https://doi.org/10.1016/j.compag.2022.107035