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FACTORS AFFECTING THE INTENTION TO ADOPT ARTIFICIAL INTELLIGENCE (AI) IN THE BUSINESS OPERATIONS OF AGRICULTURAL ENTERPRISES IN HO CHI MINH CITY

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ABSTRACT

Artificial Intelligence (AI) has become a key element in the survival and growth of businesses over the past few decades, especially in agriculture. This research aims to investigate the cognitive factors, such as Perceived Usefulness (PU), Perceived Ease of Use (PE), Effort Expectancy (EE), and Facilitating Condition (FC), influencing the Intention to adopt Artificial Intelligence (IU) in the business operations of agricultural enterprises in Ho Chi Minh City. Furthermore, the authors also seek to clarify the mediating role of Attitude toward AI Adoption (AT) in the relationship between these cognitive factors and IU. In this regard, an online survey was conducted among 251 respondents, including managers, specialists, and employees working in agricultural companies in Ho Chi Minh City. The Partial Least Squares (PLS) Smart was used to analyze the data. The findings of this study indicate that PU significantly positively affects IU and AT, while AT serves as a mediator in the relationship between PU and IU. Similarly, FC also has a positive impact on AT, and AT also plays a mediating role in the relationship between FC and IU. Unfortunately, the research results do not support the significant impact of PE and EE on AT. Based on the research findings, the authors suggest managerial implications to assist agricultural enterprises in Ho Chi Minh City deeply understand the key elements and practical benefits of AI integration in their business operations. Consequently, the study's findings help enterprises know how they can use AI technology to support achieving their business goals and build their operational strategies in a better and more appropriate way.

Keywords: AI adoption intention, perceived usefulness, perceived ease of use, effort expectancy, facilitating condition, AI attitude, agricultural enterprises.

1. INTRODUCTION

1.1. Background

In the era of digital transformation, artificial intelligence (AI) has emerged as a core technology capable of creating competitive advantages for firms through data analytics, process automation, and decision support [1]. The growing diffusion of AI has significantly reshaped business operations worldwide, with applications expanding across demand forecasting, supply chain optimization, process automation, and strategic decision-making [2]. Beyond improving operational efficiency, AI adoption is increasingly recognized as a strategic driver of firm competitiveness in highly dynamic and uncertain market environments.

However, as argued by Porter [3] and the resource-based view proposed by Barney [4], the mere possession of technology does not automatically translate into superior organizational performance. Instead, the value of technology depends on whether firms possess adequate organizational capabilities and favorable implementation conditions. This issue is particularly salient in the agricultural sector, where businesses often face substantial constraints in terms of financial resources, technological infrastructure, and the quality of human capital. Consequently, despite its transformative potential, the adoption of AI in agriculture continues to face considerable challenges [5].

In agriculture, AI is widely regarded as a key enabler of the transition from traditional production systems toward modern, smart, and sustainable agriculture. Its applications include production management, weather and disease forecasting, resource-use optimization, and the enhancement of agricultural product distribution and market access [5]. Nevertheless, in developing countries such as Vietnam, AI adoption in agricultural business activities remains limited. Major barriers include financial constraints, insufficient digital infrastructure, limited workforce capabilities, and the low level of organizational readiness to adopt emerging technologies.

1.2. Research gap

Despite the increasing scholarly attention devoted to AI adoption and digital transformation, several important research gaps remain unresolved in the current literature. Firstly, prior studies have predominantly focused on AI adoption within manufacturing, finance, healthcare, and technology-oriented industries, whereas relatively limited attention has been paid to the agricultural sector [6-9], particularly in developing economies such as Vietnam. As a result, empirical understanding of the determinants of AI adoption in agricultural enterprises remains limited.

Secondly, although the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been extensively utilized to explain technology adoption behavior, prior studies have generally applied these theoretical frameworks separately. Research integrating constructs from both perspectives to explain AI adoption intention in agricultural business operations remains scarce. In particular, the combined effects of Perceived Usefulness (PU), Perceived Ease of Use (PE), Effort Expectancy (EE), and Facilitating Conditions (FC) on AI adoption intention (IU) have not been sufficiently investigated in the agricultural context.

Thirdly, previous studies have mainly concentrated on the direct effects of technological perception variables on behavioral intention, while the underlying cognitive and attitudinal mechanisms have received comparatively less attention. Specifically, limited empirical evidence exists regarding the mediating role of Attitude toward AI Adoption (AT) in explaining how firms' technological perceptions influence their intention to adopt AI in business operations. Understanding this mechanism is essential, as organizational attitudes toward AI may play a critical role in shaping firms' readiness to adopt emerging technologies.

Finally, most prior research has been conducted in developed countries with relatively advanced digital infrastructure and technological readiness. Consequently, the generalizability of these findings to developing economies remains uncertain due to contextual differences in organizational capability, financial resources, technological infrastructure, and workforce readiness. Accordingly, further research is needed to examine AI adoption behavior within agricultural enterprises in emerging economies such as Vietnam.

To address these limitations, this study aims to investigate the cognitive factors such as perceived usefulness, perceived ease of use, effort expectancy, facilitating conditions, and attitude toward AI adoption, that influence agricultural enterprises' intention to adopt artificial intelligence (AI) in business operations in Ho Chi Minh City. Furthermore, the study seeks to examine the mediating role of attitude toward AI adoption in the relationships between cognitive factors, including perceived usefulness, perceived ease of use, effort expectancy, and facilitating conditions, and the intention to adopt AI. Based on the empirical findings, the study offers practical implications to help agricultural enterprises in Ho Chi Minh City better understand the practical benefits and key determinants of AI adoption, thereby supporting the development of appropriate investment and technology implementation strategies.

1.3. Research questions

The study aims to address fifteen questions, including:

Question 1: Does Perceived Usefulness positively influence Attitude toward AI adoption in business operations?

Question 2: Does Perceived Usefulness positively influence Intention to adopt AI in business operations?

Question 3: Does Attitude toward AI adoption mediate the relationship between Perceived Usefulness and Intention to adopt AI in business operations?

Question 4: Does Perceived Ease of Use positively influence Attitude toward AI adoption in business operations?

Question 5: Does Perceived Ease of Use positively influence Intention to adopt AI in business operations?

Question 6: Does Perceived Ease of Use positively influence Perceived Usefulness of AI in business operations?

Question 7: Does Attitude toward AI adoption mediate the relationship between Perceived Ease of Use and Intention to adopt AI in business operations?

Question 8: Does Perceived Usefulness mediate the relationship between Perceived Ease of Use and Attitude toward AI adoption in business operations?

Question 9: Does Perceived Usefulness mediate the relationship between Perceived Ease of Use and Intention to adopt AI in business operations?

Question 10: Does Effort Expectancy positively influence Attitude toward AI adoption in business operations?

Question 11: Does Effort Expectancy positively influence Intention to adopt AI in business operations?

Question 12: Does Attitude toward AI adoption mediate the relationship between Effort Expectancy and Intention to adopt AI in business operations?

Question 13: Do Facilitating Conditions positively influence firms' Attitude toward AI adoption in business operations?

Question 14: Do Facilitating Conditions positively influence Intention to adopt AI in business operations?

Question 15: Does Attitude toward AI adoption mediate the relationship between Facilitating Conditions and Intention to adopt AI in business operations?

2. THEORETICAL BACKGROUND

2.1. Related concepts

According to Arakpogun et al. [10] defined artificial intelligence (AI) as a set of information and communication technologies (ICTs) that simulate human intelligence, primarily aiming to improve work performance, enhance efficiency, and stimulate economic growth. In the business domain, agricultural enterprises are understood as organized business entities that employ resources such as capital, labor, and technology to improve productivity, operational efficiency, and competitiveness [1]. This view emphasizes the importance of agricultural enterprises in adopting innovation and technological advancement to support sustainable development. Within the agribusiness context, AI extends beyond merely replicating human intelligence; it functions as an enabling technology that supports agricultural enterprises in analyzing environmental data, generating forecasts, issuing weather and price alerts, optimizing crop cultivation and livestock management, and enhancing the quality of managerial decision-making. Accordingly, AI can be considered one of the key technologies underpinning digital transformation and innovation in the contemporary business activities of agricultural enterprises.

Based on Eli-Chukwu et al. [11] suggested that the application of artificial intelligence (AI) in agribusiness encompasses the use of machine learning algorithms, big data analytics, and automated systems to support functions such as yield forecasting, supply chain management, distribution optimization, and improved agricultural marketing performance. This view underscores the role of AI as a strategic enabler in the management and development of agricultural enterprises. As such, the perceived strategic value of AI may shape how agricultural firms evaluate its usefulness, develop favorable attitudes, and form intentions toward its adoption.

2.2. Theoretical background

Among the major theoretical frameworks used to explain technology adoption, the Technology Acceptance Model (TAM) has been one of the most influential models in information systems research [12-14]. TAM emphasizes two core beliefs—perceived ease of use and perceived usefulness—which influence users' attitudes and subsequently their behavioral intentions toward adopting new technologies. In its original formulation [15] positioned behavioral intention as a key determinant of actual system use, directly influenced by attitude toward use and perceived usefulness.

In addition, the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) provide complementary perspectives for understanding technology adoption behavior. TRA explains that attitude toward a behavior and subjective norms jointly shape an individual's behavioral intention [16]. Therefore, this study adopts TAM and TRA as the main theoretical foundations for developing the proposed research model.

Furthermore, this study integrates the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to provide a more comprehensive explanation of AI adoption behavior in agricultural enterprises. While TAM focuses on individual cognitive evaluations of technology, particularly perceived usefulness and perceived ease of use [15], UTAUT extends this framework by incorporating additional determinants such as effort expectancy and facilitating conditions [17].

The integration is justified because AI adoption in business operations involves not only individual perceptions but also organizational and contextual factors. In particular, facilitating conditions reflect the role of technological infrastructure and organizational support, which are critical in enterprise settings [17]. Therefore, combining TAM and UTAUT enables this study to capture both individual-level and organizational-level determinants of AI adoption.

It is important to distinguish between perceived ease of use (PE) and effort expectancy (EE), as these constructs originate from different theoretical perspectives. Perceived ease of use refers to the degree to which a system is perceived as easy to use, as defined in TAM [15]. In contrast, effort expectancy reflects the perceived level of effort required to learn and apply technology in practice, particularly in organizational contexts [17]. In the context of AI adoption, effort expectancy captures organizational concerns such as implementation complexity, required training, and system integration, whereas perceived ease of use mainly reflects individual interaction with the system interface.

2.3. Proposed model and Hypotheses

According to the Unified Theory of Acceptance and Use of Technology (UTAUT), Effort Expectancy (EE) refers to the degree of ease associated with the use of technology [17]. In the context of agricultural enterprises, effort expectancy reflects the extent to which firms perceive AI systems as requiring manageable levels of effort in terms of learning, implementation, and operation. According to the Technology Acceptance Model (TAM), Perceived Usefulness (PU) refers to the extent to which an individual believes that using a particular system will enhance job performance [15]. In the organizational context, PU reflects the extent to which firms believe that technology can improve productivity, reduce costs, and strengthen competitive advantage [17]. For agricultural enterprises in Ho Chi Minh City, whose production and business activities are heavily influenced by yield forecasting, supply chain coordination, and market volatility, AI adoption may facilitate data analysis, optimize operational processes, and improve managerial effectiveness. When firms perceive that AI offers substantial and practical benefits to their business operations, they are more likely to develop a favorable attitude toward AI adoption [18], which subsequently increases their intention to adopt AI in business activities. Accordingly, the following hypotheses are proposed:

Hypothesis H_{1a}: Perceived Usefulness has a positive effect on Attitude toward AI adoption in business operations.

Hypothesis H_{1b}: Perceived Usefulness has a positive effect on Intention to adopt AI in business operations.

Hypothesis H_{1c}: Attitude toward AI adoption mediates the relationship between Perceived Usefulness and Intention to adopt AI in business operations.

Perceived Ease of Use (PE) is defined as the degree to which an individual believes that using a particular system would be free of effort and easy to understand [15]. In the context of agricultural enterprises, where technological capabilities and workforce competencies may vary considerably, the complexity of AI systems may constitute a substantial barrier to adoption [17]. Accordingly, when AI solutions are designed to be user-friendly, easy to implement, and compatible with the operational capacities of agricultural firms, they are more likely to reduce uncertainty and resistance while enhancing acceptance. Prior studies grounded in the Technology Acceptance Model (TAM) further indicate that systems perceived as easier to use tend to foster more favorable attitudes toward adoption [19]. Based on these arguments, the following hypotheses are developed.

Hypothesis H_{2a}: Perceived Ease of Use has a positive effect on Attitude toward AI adoption in business operations.

Hypothesis H_{2b}: Perceived Ease of Use has a positive effect on Intention to adopt AI in business operations.

Hypothesis H_{2c}: Perceived Ease of Use has a positive effect on Perceived Usefulness of AI in business operations.

Hypothesis H_{2d}: Attitude toward AI adoption mediates the relationship between Perceived Ease of Use and Intention to adopt AI in business operations.

Hypothesis H_{2e}: Perceived Usefulness mediates the relationship between Perceived Ease of Use and Attitude toward AI adoption in business operations.

Hypothesis H_{2f}: Perceived Usefulness mediates the relationship between Perceived Ease of Use and Intention to adopt AI in business operations.

According to the Unified Theory of Acceptance and Use of Technology (UTAUT) [17], Effort Expectancy (EE) is defined as the degree to which an individual believes that using a particular technology will help achieve gains in job performance [20]. In the context of agricultural enterprises, such expected performance gains may include improved farming productivity, enhanced product quality, more efficient inventory management, and stronger market forecasting capabilities. Accordingly, when agricultural enterprises in Ho Chi Minh City perceive that AI can enhance business performance and improve their ability to respond to market volatility, they are more likely to develop a favorable attitude toward AI adoption.

Hypothesis H_{3a}: Effort Expectancy has a positive effect on Attitude toward AI adoption in business operations.

Hypothesis H_{3b}: Effort Expectancy has a positive effect on Intention to adopt AI in business operations.

Hypothesis H_{3c}: Attitude toward AI adoption mediates the relationship between Effort Expectancy and their Intention to adopt AI in business operations.

According to the Unified Theory of Acceptance and Use of Technology (UTAUT), Facilitating Conditions (FC) refer to the extent to which individuals believe that the organizational and technical infrastructure necessary to support the use of technology is in place [19]. In the context of agricultural enterprises in Ho Chi Minh City, AI adoption requires an adequate data infrastructure, compatible technological systems, sufficient financial resources, and support from top management. Accordingly, when firms perceive that they have sufficient resources, infrastructure, and supportive organizational policies to implement AI, they are more likely to develop a favorable attitude toward AI adoption because the perceived level of implementation risk is reduced.

Hypothesis H_{4a}: Facilitating Conditions have a positive effect on firms' Attitude toward AI adoption in business operations.

Hypothesis H_{4b}: Facilitating Conditions have a positive effect on Intention to adopt AI in business operations.

Hypothesis H_{4c}: Attitude toward AI adoption mediates the relationship between Facilitating Conditions and Intention to adopt AI in business operations.

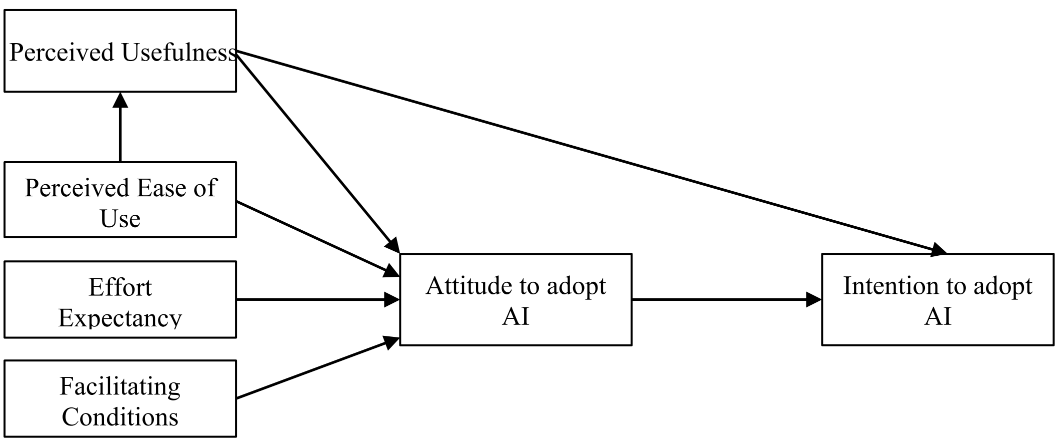

Figure 1. Proposed Research Model. Source: Authors' elaboration

3. METHODOLOGY

This study adopted a quantitative approach, with preliminary expert consultation to refine the measurement scales before administering the main survey. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used as the primary analytical technique due to its suitability for complex models and prediction-oriented research [21].

3.1. Measurement Development

In the first stage, the authors reviewed prior literature to establish the conceptual framework and adapt the measurement scales from previous studies, then a comprehensive literature review was conducted to establish the conceptual framework and to identify relevant constructs.The measurement scales were adapted from prior studies grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which are widely used in technology adoption research [15], [17], [19]. Specifically, Perceived Usefulness (PU) and Perceived Ease of Use (PE) were adapted from TAM [15], while Effort Expectancy (EE) and Facilitating Conditions (FC) were derived from UTAUT [17]. Attitude toward AI adoption (AT) was based on attitude theory [16], and Intention to Adopt AI (IU) was adapted from prior technology adoption studies [18]. To ensure content validity and contextual relevance, the initial measurement items were reviewed and refined through expert consultation prior to the survey data collection.

3.2. Expert Review of Measurement Scales

In the second stage, before conducting the main survey, the questionnaire was evaluated by a panel of experts to ensure clarity, relevance, and appropriateness for the context of agricultural enterprises. A total of 8 experts participated in this stage, involving researchers, executives, business owners, and specialists from agricultural enterprises to refine the measurement items and finalize the survey questionnaire. The experts were selected based on the following criteria (1) professional experience related to AI implementation or digital transformation, (2) familiarity with agricultural business operations, and (3) involvement in managerial or technical decision-making processes. Based on the feedback obtained from these experts, several measurement items were adjusted to improve wording clarity, eliminate ambiguity, and enhance contextual suitability. This pre-testing procedure is consistent with established practices in scale development and adaptation in technology adoption research [17].

3.3. Data Collection

In the final stage, the main data collection was carried out using an online survey with the finalized questionnaire. All items were measured on a Seven-point Likert scale ranging from strongly disagree to strongly agree. The survey instrument included screening questions and measurement items corresponding to six constructs in the research model (see Fig.1), namely Perceived Usefulness (PU, 5 indicators), Perceived Ease of Use (PE, 4 indicators), Effort Expectancy (EE, 4 indicators), Facilitating Conditions (FC, 4 indicators), Attitude toward AI Adoption (AT, 3 indicators), and Intention to Adopt AI (IU, 3 indicators). The responses collected were coded and prepared for data analysis.

3.4. Data Analysis

The data collected were analyzed using SmartPLS software. PLS-SEM was selected because of its advantages in handling complex structural models and relatively small sample sizes [21], [22]. The analysis procedure consisted of two main stages. First, the measurement model was assessed to examine reliability and validity. Convergent and discriminant validity were evaluated based on the criteria proposed by Fornell and Larcker [23] and Henseler et al. [24]. Second, the structural model was evaluated to test the proposed hypotheses. In addition, multicollinearity and model robustness were examined following the guidelines suggested by

Kock and Mayfield [25]. Based on the empirical results, managerial implications were proposed to support AI adoption in agricultural enterprises.

4. RESULTS AND DISCUSSION

4.1. Sample Description

A total of 260 online survey responses were initially collected. After screening and removing 9 invalid responses, the final sample consisted of 251 valid respondents from agricultural enterprises in Ho Chi Minh City, Vietnam. As shown in Table 1, the gender distribution was relatively balanced, with 125 male respondents (49.8%) and 126 female respondents (50.2%). In terms of age, age groups from 31 to 35 accounted for the largest share of the sample (30.7%, n = 77), whereas the range of age groups from 36 to 40 represented the smallest share (n = 14). Regarding educational background, most respondents held a bachelor's degree (71.3%, n = 179), followed by a master's degree (17.1%, n = 43). Meanwhile, 10.0% of respondents (n = 25) reported other qualifications, and only 1.6% (n = 4) held a doctoral degree.

Table 1. Descriptive statistics

Group	No.	Content	Count	Percentage (%)
Gender	1	Male	125	49.8
	2	Female	126	50.2
		Total	251	100%
Age	1	18 - 20	49	19.5
	2	21 - 25	29	11.6
	3	26 - 30	21	8.4
	4	31 - 35	77	30.7
	5	36 - 40	14	5.6
	6	Above 40	61	24.3
		Total	251	100%
Education	1	Bachelor	179	71.3
	2	Master	43	17.1
	3	Ph.D	4	1.6
	4	Others	25	10.0
		Total	251	100%
Experience	1	Under 3 years	73	29.1
	2	3 – under 5 years	70	27.9
	3	5 – under 10 years	50	19.9
	4	Above 10 years	58	23.1
		Total	251	100%
Scale	1	Below 10 employees	65	25.9
	2	10 – below 20 employees	41	16.3
	3	20 – below 30 employees	78	31.1
	4	30 – under 40 employees	67	26.7

Group	No.	Content	Count	Percentage (%)
		Total	251	100%

Source: Authors

With respect to work experience, respondents with less than three years of experience constituted the largest group (29.1%, n = 73), followed by those with three to less than five years of experience (27.9%, n = 70). Meanwhile, respondents with 10 years or more of work experience accounted for 23.1% of the sample (n = 58), while those with five to less than ten years of experience represented the smallest proportion (19.9%, n = 50).

In terms of firm size, most surveyed enterprises employed 20 to less than 30 employees (31.1%, n = 78), followed by firms with 30 to less than 40 employees (26.7%, n = 67). In addition, 25.9% of enterprises (n = 65) had fewer than 10 employees, whereas 16.3% (n = 41) employed 10 to less than 20 employees.

4.2. Evaluation of Measurement Model

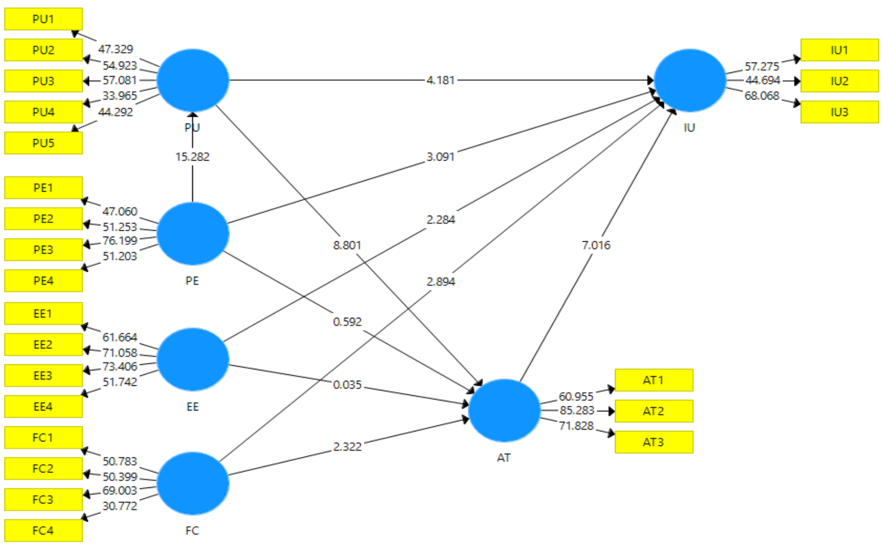

Figure 2. The nonogram of the Adjusted Model. Source: Authors

4.2.1. Indicator reliability

In this section, the reliability of the measurement indicators was assessed. According to Hair et al. [21], evaluating indicator reliability is necessary to determine whether the observed variables within each construct adequately represent the corresponding latent construct. In PLS-SEM, indicators with outer loadings of 0.70 or higher are considered acceptable, while those with loadings below 0.40 should be removed. For indicators with loadings between 0.40 and 0.70, the decision to retain or exclude them should be made based on their contribution to the construct's overall reliability and validity. The results show that the outer loadings of all indicators were above 0.70, confirming satisfactory indicator reliability.

4.2.2. Scale reliability and Convergent validity

Subsequently, the internal consistency reliability of the constructs was examined using Cronbach's alpha, composite reliability (rho_A), and composite reliability (rho_C). Following Hair et al. [21], values of 0.70 or above indicate satisfactory reliability, values of 0.60 or above may be acceptable in certain cases, particularly in exploratory studies, whereas values exceeding 0.95 may indicate potential item redundancy. According to Table 2, all reliability estimates were above 0.70 and below 0.95, confirming that the measurement scales demonstrated adequate internal consistency reliability.

Table 2. Construct Reliability and Validity

	Cronbach's Alpha	rho_A	Composite Reliability	AVE
AT	0.916	0.917	0.947	0.857
EE	0.928	0.929	0.949	0.823
FC	0.906	0.907	0.935	0.781
IU	0.893	0.893	0.933	0.823
PE	0.914	0.915	0.939	0.795
PU	0.936	0.936	0.950	0.795

Source: Authors

Furthermore, convergent validity was evaluated using the Average Variance Extracted (AVE). According to Hock and Ringle [22], an AVE value of 0.50 or higher indicates that a construct explains at least 50% of the variance in its indicators and is therefore considered acceptable. As reported in Table 2, all constructs exhibited AVE values above 0.50, confirming that the measurement model achieved satisfactory convergent validity.

4.2.3. Discriminant validity (Fornell and Larcker, HTMT)

Subsequently, discriminant validity was examined to ensure that each latent construct was distinct from the other constructs in the model. This was assessed using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). Following Fornell and Larcker [23], the correlation between any two constructs should be lower than the square root of the AVE of each construct involved in the comparison. In addition, Henseler et al. [24] suggested that HTMT values below 0.90 indicate acceptable discriminant validity. In Tables 3 and 4, the results show that all constructs met both criteria, thereby confirming adequate discriminant validity and indicating that the measurement model was suitable for subsequent structural model assessment.

Table 3. Fornell-Larcker

	AT	EE	FC	IU	PE	PU
AT	0.926					
EE	0.619	0.907				
FC	0.649	0.804	0.884			
IU	0.820	0.644	0.683	0.907		
PE	0.609	0.840	0.740	0.548	0.892	
PU	0.743	0.689	0.675	0.770	0.670	0.892

Source: Authors

Table 4. HTMT ratio

	AT	EE	FC	IU	PE	PU
AT						
EE	0.670					
FC	0.709	0.776				

IU	0.889	0.706	0.757		
PE	0.664	0.893	0.813	0.604	
PU	0.803	0.738	0.731	0.842	0.723

Source: Authors

4.3. Evaluation of Structural Model

4.3.1. VIF (Collinearity)

To assess potential multicollinearity in the measurement model, the authors examined the variance inflation factor (VIF) values of the indicators based on the guideline proposed by Hair et al. [21]. According to this recommendation, VIF values below 3.0 indicate that collinearity is not a critical issue. The results show that the VIF values for all measurement indicators, including PU1, PU2, PU3, PU4, PE1, PE2, PE3, PE4, EE1, EE2, EE3, EE4, FC1, FC2, FC3, FC4, AT1, AT2, AT3, IU1, IU2, IU3, are below the threshold of 3.0. These findings suggest that no multicollinearity problem is present in the measurement model.

Common method bias (CMB) was assessed through the examination of the inner model's Variance Inflation Factor (VIF) values. Based on the criterion proposed by Ned Kock [25], VIF values below 3.33 indicate the absence of substantial common method variance. Given that all VIF values in the present study were below the recommended cutoff, common method bias was deemed unlikely to affect the validity of the results.

4.3.2. Path Coefficients

Based on the bootstrapping results presented in Table 5, attitude toward AI adoption (AT) was found to have a direct positive and statistically significant effect on intention to adopt AI (IU) ($\beta = 0.513$, $p < 0.001$). Meanwhile, effort expectancy (EE) showed a positive and statistically significant effect on IU ($\beta = 0.182$, $p = 0.017$). However, the results did not support the relationship between EE and AT ($\beta = -0.005$, $p = 0.973$). Similarly, perceived ease of use (PE) was not found to significantly influence AT. Nevertheless, PE had a positive and statistically significant effect on perceived usefulness (PU) ($\beta = 0.670$, $p < 0.001$) and a negative but statistically significant effect on IU ($\beta = -0.270$, $p = 0.002$). In addition, the remaining two constructs, facilitating conditions (FC) and perceived usefulness (PU), both exhibited positive and statistically significant effects on AT and IU, respectively.

Table 5. Path Coefficients

	Original Sample	Sample Mean	Standard Deviation	T- Statistic	p-value
AT -> IU	0.513	0.513	0.075	6.820	0.000
EE -> AT	-0.005	0.011	0.133	0.034	0.973
EE -> IU	0.182	0.174	0.076	2.399	0.017
FC -> AT	0.228	0.232	0.100	2.294	0.022
FC -> IU	0.190	0.186	0.065	2.925	0.004
PE -> AT	0.085	0.072	0.151	0.560	0.576
PE -> IU	-0.270	-0.257	0.087	3.098	0.002
PE -> PU	0.670	0.668	0.045	14.744	0.000
PU -> AT	0.536	0.532	0.061	8.752	0.000
PU -> IU	0.316	0.316	0.074	4.264	0.000

Source: Authors

In the previous section above, hypothesis H_{2b} predicted that Perceived Ease of Use would positively influence firms' intention to adopt AI in business operations. Nevertheless, the empirical analysis revealed a statistically significant but negative relationship between PE and IU ($\beta = -0.270$, $p = 0.002$). Since the direction of the relationship was inconsistent with the proposed hypothesis, H_{2b} was not supported by the data.

4.3.3. Specific Indirect Effects

Furthermore, the study assessed the indirect effects to examine the mediating role of attitude toward AI adoption (AT) in the relationships between PU, PE, EE, FC, and IU. In addition, the mediating role of perceived usefulness (PU) was evaluated in the relationship between PE and IU, as well as between PE and AT.

The results reported in Table 6 reveal that AT serves as a significant mediator in the relationships between FC and IU and between PU and IU. However, the indirect effects of PE and EE on IU through AT are not statistically significant, indicating that the mediating role of AT is not supported in these two relationships ($p > 0.05$). In contrast, PU significantly mediates the relationship between PE and IU ($\beta = 0.212$, $p < 0.001$) as well as the relationship between PE and AT ($\beta = 0.359$, $p < 0.001$).

Table 6. Specific Indirect Effects

	Original Sample	Sample Mean	Standard Deviation	T- Statistic	p-value
FC -> AT -> IU	0.117	0.120	0.056	2.082	0.038
PE -> AT -> IU	0.043	0.032	0.076	0.569	0.570
PU -> AT -> IU	0.275	0.273	0.051	5.373	0.000
EE -> AT -> IU	-0.002	0.010	0.069	0.034	0.973
PE -> PU -> IU	0.212	0.211	0.049	4.309	0.000
PE -> PU -> AT	0.359	0.356	0.047	7.593	0.000

Source: Authors

The inclusion of mediation analysis involving AT and PU substantially improves the theoretical rigor of the proposed research model. The results presented in Table 6 demonstrate that AT significantly mediates the relationships between FC and IU, as well as between PU and IU. Notably, the indirect effect of PU on IU through AT was statistically significant and relatively strong, emphasizing the importance of attitude as a key psychological mechanism linking perceived technological benefits to adoption intention. Furthermore, the findings indicate that PU serves as a significant mediator in the relationship between PE and both AT and IU. This suggests that enterprises' expectations regarding the performance-enhancing capabilities of AI technologies indirectly influence attitudes and adoption intention through increased perceptions of usefulness. Taken together, these mediation effects provide deeper insight into the cognitive and attitudinal mechanisms underlying AI adoption behavior. By incorporating both AT and PU as mediating constructs, the study offers a more comprehensive explanation of how technological perceptions are translated into behavioral intention, thereby reinforcing the integration of TAM and UTAUT within the context of AI adoption in agricultural enterprises.

4.3.4. R-square and f (effect side)

The coefficient of determination (R^2) reflects the proportion of variance in an endogenous construct that can be explained by its corresponding predictor variables in the structural model. As shown in the results, the adjusted R^2 values are 0.589 for AT, 0.788 for IU, and 0.447 for

PU. This indicates that the latent variables included in the model explain 78.8% of the variance in IU, 58.9% of the variance in AT, and 44.7% of the variance in PU, respectively.

In Table 7, the authors present a summary of the hypothesis testing outcomes for all proposed relationships in the study. The results show that 11 out of 15 hypotheses are supported, while the remaining 4 hypotheses are not supported.

Table 7. Summary of the Hypothesis Testing

No	Hypothesis	Direct and Indirect Path	p-value	Supported
1	H_{1a}	PU -> AT	0.000	Supported
2	H_{1b}	PU -> IU	0.000	Supported
3	H_{1c}	PU -> AT -> IU	0.000	Supported
4	H_{2a}	PE -> AT	0.576	Not supported
5	H_{2b}	PE -> IU	0.002	Not supported
6	H_{2c}	PE -> PU	0.000	Supported
7	H_{2d}	PE -> AT -> IU	0.570	Not supported
8	H_{2e}	PE -> PU -> AT	0.000	Supported
9	H_{2f}	PE -> PU -> IU	0.000	Supported
10	H_{3a}	EE -> AT	0.973	Not supported
11	H_{3b}	EE -> IU	0.017	Supported
12	H_{3c}	EE -> AT -> IU	0.973	Not supported
13	H_{4a}	FC -> AT	0.022	Supported
14	H_{4b}	FC -> IU	0.004	Supported
15	H_{4c}	FC -> AT -> IU	0.038	Supported

Source: Authors

5. CONCLUSION

The findings suggest several important recommendations for promoting AI adoption in the business operations of agricultural enterprises. Firstly, organizations should prioritize enhancing Perceived Usefulness of AI (PU), as it is the strongest predictor of both Attitude towards AI adoption (AT) and Intention to adopt AI (IU). Enterprises should therefore emphasize the tangible benefits of AI, such as improved efficiency, better decision-making, and stronger competitive performance. Secondly, the findings provide an unexpected insight into the relationship between Perceived Ease of Use of AI (PE) and firms' intention to adopt AI in business operations. This result contradicts the traditional assumptions of TAM, in which ease of use is typically expected to positively influence adoption intention [15]. Consistent with the Technology Acceptance Model (TAM), prior studies have generally reported that technologies perceived as easier to use are more likely to be accepted and adopted. However, the present study identified a significant negative effect of PE on AI adoption intention, suggesting that higher perceptions of AI ease of use do not necessarily translate into stronger adoption intentions among agricultural enterprises. A possible explanation is that, in the context of AI technologies, systems perceived as overly simple may be interpreted as lacking sophistication or advanced capabilities. In agricultural enterprises, AI is often associated with complex analytics, automation, and intelligent decision-making tools [11]. Therefore, technologies that appear too easy to use may be perceived as less powerful or less suitable for strategic business applications. This finding suggests that, in certain contexts, perceived complexity may signal higher technological value, leading to a negative relationship between perceived ease of use and adoption intention. Moreover, the non-significant relationships between perceived ease of use and attitude, as well as between effort expectancy and attitude, suggest that firms' attitudes toward AI adoption are primarily driven by perceived benefits rather than usability factors. This finding aligns with prior research indicating that organizations tend to prioritize performance-related outcomes when evaluating advanced technologies [12], [13]. In the context of AI adoption, decision-makers may focus more on the expected contributions of the technology to efficiency, productivity, and competitive advantage rather than on ease of use. Thirdly, by contrast, Effort Expectancy (EE) was found to exert a significant influence on AI adoption intention. This finding supports the Unified Theory of Acceptance and Use of Technology (UTAUT), which posits that organizations are more inclined to adopt emerging technologies when they perceive the effort required for learning and implementation to be reasonable and manageable. Fourthly, given the significant role of Facilitating Condition (FC), firms should invest in technical infrastructure, organizational support, and leadership commitment to create an enabling environment for AI adoption. Finally, since AT mediates the effects of PU and FC on IU, managers should actively foster positive employee attitudes by framing AI as a supportive and value-creating technology rather than a disruptive threat. Collectively, these strategies can enhance organizational readiness and strengthen the successful adoption of AI in the business operations of agricultural enterprises. Finally, the mediation analysis provides deeper insights into the cognitive and attitudinal mechanisms underlying AI adoption. The significant mediating role of attitude between perceived usefulness and intention confirms that cognitive evaluations are translated into behavioral intentions through affective responses, consistent with attitude-behavior theory [16]. Furthermore, the results demonstrate that perceived usefulness plays a crucial mediating role in the relationship between perceived ease of use and both attitude and intention. This finding reinforces the central role of perceived usefulness in TAM, suggesting that ease of use indirectly influences adoption through its impact on perceived benefits [15]. In contrast, the mediating role of attitude was not supported in the relationships involving perceived ease of use and effort expectancy, indicating that these factors do not substantially influence intention through attitudinal pathways.

From a managerial perspective, the findings provide meaningful implications for managers, and AI technology providers in the agricultural sector. Business leaders should develop comprehensive digital transformation strategies that embed AI technologies into core operational activities, including production management, supply chain optimization, customer relationship management, and predictive analytics. In addition, organizations should implement continuous AI training and upskilling programs to strengthen employees' technological competencies and reduce resistance to organizational change. Managers are also encouraged to cultivate an innovation-oriented organizational culture that supports experimentation, collaborative learning, and the effective implementation of AI technologies.

From a theoretical standpoint, this study enriches existing literature by integrating key constructs from the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain AI adoption intention within agricultural enterprises. The study also contributes to prior research by confirming the mediating role of attitude toward AI adoption in the relationships between technological perception factors and behavioral intention. This study also contributes to the literature by extending the application of TAM and UTAUT to the context of AI adoption in agricultural enterprises, which remains relatively underexplored. Previous studies have primarily focused on consumer technologies or general organizational adoption [8], whereas this study provides empirical evidence on AI adoption within a specific and economically important sector. In addition, the study highlights the distinct roles of perceived ease of use and effort expectancy, as well as the mediating effects of perceived usefulness and attitude, thereby offering a more comprehensive understanding of technology adoption mechanisms [15], [17].

While this study contributes to the growing literature on AI adoption in agricultural enterprises, several limitations should be recognized. Firstly, the empirical investigation was limited to agricultural enterprises operating within a specific geographical context, potentially constraining the generalizability of the findings to other industrial sectors or international settings. Future research could address this limitation by undertaking cross-industry and cross-cultural comparative analyses. Secondly, this study mainly focused on individual perception-based determinants of AI adoption intention. Other organizational and environmental factors, including organizational culture, innovation capability, financial readiness, competitive pressure, and institutional support, were not incorporated into the conceptual framework. Incorporating these variables in future research may provide a more comprehensive understanding of the mechanisms underlying AI adoption behavior.

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REFERENCES

[1] Organisation for Economic Co-operation and Development (OECD), Digital Opportunities for Better Agricultural Policies. Paris, France: OECD Publishing, 2019, doi: https://doi.org/10.1787/571a0812-en

[2] C. Zhang and Y. Lu, “Study on artificial intelligence: The state of the art and future prospects,” Journal of Industrial Information Integration, vol. 23, Art. no. 100224, 2021, doi: https://doi.org/10.1016/j.jii.2021.100224

[3] M. E. Porter, “Technology and competitive advantage,” Journal of Business Strategy, vol. 5, no. 3, pp. 60–78, 1985, doi: https://doi.org/10.1108/eb039075

[4] Barney, “Firm resources and sustained competitive advantage,” Journal of Management, vol. 17, no. 1, pp. 99–120, 1991, doi: https://doi.org/10.1177/014920639101700108

[5] UNICEF, The State of Food Security and Nutrition in the World 2024: Financing to End Hunger, Food Insecurity and Malnutrition in All Its Forms, 2024. doi: https://doi.org/10.4060/cd1254en

[6] D. J. Leybourne, N. Musa, and P. Yang, “Can artificial intelligence be integrated into pest monitoring schemes to help achieve sustainable agriculture? An entomological, management and computational perspective,” Agricultural and Forest Entomology, vol. 27, no. 1, pp. 8–17, 2025, doi: https://doi.org/10.1111/afe.12630

[7] H. T. Hung and N. N. Hien, “Nghiên cứu ý định sử dụng của người tiêu dùng đối với nền tảng thương mại điện tử có tích hợp trí tuệ nhân tạo (AI),” Journal of Science and Technology-IUH, vol. 75, no. 3, 2025, doi: https://doi.org/10.46242/jstiuh.v75i3.5196

[8] N. A. H. E. Ahmed, M. Benhada, and M. Chegrani, “Adopting artificial intelligence in entrepreneurial ecosystems: An analytical assessment of digital readiness among young entrepreneurs in Algeria,” Science, Education and Innovations in the Context of Modern Problems, vol. 9, no. 6, pp. 1–17, 2026, doi: https://doi.org/10.56334/sei/9.6.1

[9] D. Shadrin, A. Menshchikov, D. Ermilov, and A. Somov, “Designing future precision agriculture: Detection of seeds germination using artificial intelligence on a low-power embedded system,” IEEE Sensors Journal, vol. 20, no. 10, pp. 5603–5612, 2020, doi: https://doi.org/10.1109/JSEN.2019.2935812

[10] E. O. Arakpogun, Z. Elsahn, F. Olan, and F. Elsahn, "Artificial intelligence in Africa: Challenges and opportunities," in The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success, 2021, pp. 375–388, doi: https://doi.org/10.1007/978-3-030-62796-6_22

[11] N. C. Eli-Chukwu, "Applications of artificial intelligence in agriculture: A review," Engineering, Technology and Applied Science Research, vol. 9, no. 4, 2019, doi: https://doi.org/10.48084/etasr.2756

[12] S. H. W. Chuah *et al.,* "Wearable technologies: The role of usefulness and visibility in smartwatch adoption," Computers in Human Behavior, vol. 65, pp. 276–284, 2016, doi: https://doi.org/10.1016/j.chb.2016.07.047

[13] T. Kim and W. Chiu, "Consumer acceptance of sports wearable technology: The role of technology readiness," International Journal of Sports Marketing and Sponsorship, vol. 20, no. 1, pp. 109–126, 2019, doi: https://doi.org/10.1108/IJSMS-06-2017-0050

[14] M. Jasin, H. U. Anisah, C. E. A. Fatimah, F. E. A. Azra, L. Suzanawaty, and I. W. R. Junaedi, "The role of digital literacy and knowledge management on process innovation in SMEs," International Journal of Data and Network Science, vol. 8, no. 1, pp. 337–344, 2024, doi: https://doi.org/10.5267/j.ijdns.2023.9.020

[15] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Quarterly, vol. 13, no. 3, pp. 319–340, 1989, doi: https://doi.org/10.2307/249008

[16] I. Ajzen and M. Fishbein, "Attitudes and the attitude-behavior relation: Reasoned and automatic processes," European Review of Social Psychology, vol. 11, no. 1, pp. 1–33, 2000, doi: https://doi.org/10.1080/14792779943000116

[17] M. M. Abbad, "Using the UTAUT model to understand students' usage of e-learning systems in developing countries," Education and Information Technologies, vol. 26, no. 6, pp. 7205–7224, 2021, doi: https://doi.org/10.1007/s10639-021-10573-5

[18] V. Dutot, V. Bhatiasevi, and N. Bellallahom, "Applying the technology acceptance model in a three-countries study of smartwatch adoption," The Journal of High Technology Management Research, vol. 30, no. 1, pp. 1–14, 2019, doi: https://doi.org/10.1016/j.hitech.2019.02.001

[19] V. Venkatesh and F. D. Davis, "A theoretical extension of the technology acceptance model: Four longitudinal field studies," Management Science, vol. 46, no. 2, pp. 186–204, 2000, doi: https://doi.org/10.1287/mnsc.46.2.186.11926

[20] S. Cao, W. Jiang, B. Yang, and A. L. Zhang, "How to talk when a machine is listening: Corporate disclosure in the age of AI," The Review of Financial Studies, vol. 36, no. 9, pp. 3603–3642, 2023, doi: https://doi.org/10.1093/rfs/hhad021

[21] J. Hair and A. Alamer, "Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research," Research Methods in Applied Linguistics, vol. 1, no. 3, Art. no. 100027, 2022, doi: https://doi.org/10.1016/j.rmal.2022.100027

[22] C. Hock, C. M. Ringle, and M. Sarstedt, "Management of multi-purpose stadiums," International Journal of Services Technology and Management, vol. 14, nos. 2–3, pp. 188–207, 2010, doi: https://doi.org/10.1504/IJSTM.2010.034327

[23] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," Journal of Marketing Research, vol. 18, no. 1, pp. 39–50, 1981, doi: https://doi.org/10.2307/3151312

[24] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," Journal of the Academy of

Marketing Science, vol. 43, no. 1, pp. 115–135, 2015, doi: https://doi.org/10.1007/s11747-014-0403-8

[25] N. Kock and M. Mayfield, "PLS-based SEM algorithms: The good neighbor assumption, collinearity, and nonlinearity," Information Management and Business Review, vol. 7, no. 2, pp. 113–130, 2015, doi: https://doi.org/10.22610/imbr.v7i2.1146