Factors Influencing the Adoption and Diffusion of IoT-Based Fertigation Technology Among Millennials in West Java

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ABSTRACT

This study examines the factors driving the adoption and diffusion of IoT-based fertigation technology among agricultural vocational school students in Indonesia. Using a Structural Equation Modeling-Smart PLS approach, this study analyzed data from a survey of 39 students participating in a specialized technology workshop at two leading agricultural vocational schools. The findings confirmed the significant influence of both the Technology Acceptance Model (TAM) construct and perceived learning quality on technology adoption and diffusion. The TAM showed a strong positive relationship with both diffusion (β = 0.851) and adoption (β = 0.576). While learning quality directly and positively influenced diffusion (β = 0.125), learning quality had a negative direct effect on adoption (β = -0.161) and a positive indirect effect through diffusion (β = 0.356). These results underscore the importance of positive technology perceptions and effective learning experiences in fostering the successful adoption of smart agricultural innovations among future agricultural professionals.

Keywords: technological acceptance model, Internet of Think learning quality

INTRODUCTION

In the Fourth Industrial Revolution, digitalization, particularly through the Internet of Things (IoT), plays a crucial role in improving agricultural productivity and quality of life [1]. IoT technology has become a cornerstone of smart agriculture by facilitating real-time data processing, enabling rapid responses to environmental changes, and enhancing productivity monitoring, all of which are essential for mitigating the risk of crop failure [2]. The application of technology in agriculture is also expected to encourage millennials to engage more actively in the agricultural sector. Smart agriculture has the potential to transform negative perceptions of agriculture among young people and attract them to the sector [3].

Despite these opportunities, significant challenges remain, particularly the relatively low number of millennials who choose agriculture as a career, highlighting the need for various technology dissemination initiatives. Barriers to technology dissemination, particularly technology adoption among farmers, are also influenced by several factors that contribute to the digital divide. These factors include geographical barriers, such as the urban–rural divide; socioeconomic challenges; and limited support from the government and private sector for information and communication technology (ICT) education [4]. Addressing these disparities requires the involvement of early adopters, including young people, secondary school students, office workers, and agricultural entrepreneurs.

This study examines the challenges associated with the low adoption of IoT technology in agriculture among millennials in Indonesia, particularly within the context of the Fourth Industrial Revolution. The primary objective is to assess the factors influencing the adoption and diffusion of IoT-based fertigation technology among millennials in West Java. The study was conducted in Lembang District, West Bandung Regency, which is known for its advanced urban agricultural practices, and Tanjungsari District, Sumedang Regency, which is characterized by traditional

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agricultural practices. These locations provide an appropriate setting for implementing IoT-based Smart Agriculture due to their relatively developed infrastructure. Sumedang has also been designated as an "Indonesian Digital Service Living Lab Platform" for 60 regencies and cities across Indonesia.

This study integrates the characteristics of innovation diffusion, learning quality, and technology adoption levels by employing the Unified Theory of Acceptance and Use of Technology (UTAUT) model developed [5] and Structural Equation Modeling (SEM). The SEM analysis is used to identify relationships among latent variables, evaluate indicator loading values, and estimate the structural pathways associated with IoT adoption. This study addresses a gap in the existing literature by applying SEM to examine innovation diffusion and the effectiveness of adopting IoT-based fertigation technology among millennial students.

The study aims to provide insights for improving agricultural education at the secondary school level and preparing vocational school students to develop the competencies required to build and maintain automated agricultural systems in Indonesia. The findings are expected to contribute significantly to the existing literature on technology adoption while providing practical guidance for educators, policymakers, and technology developers working in the agricultural sector.

RESEARCH METHOD

Theoretical Framework and Hypothesis Development

This study employs Structural Equation Modeling (SEM) to analyze the key factors influencing the adoption and diffusion of IoT-based fertigation technology among millennials in West Java. By incorporating both observed and latent variables, SEM provides a comprehensive understanding of the complex dynamics underlying technology adoption. The research model is grounded in Innovation Diffusion Theory (IDT) and the Technology Acceptance Model (TAM), with a particular focus on Innovation Adoption, Technology Diffusion, Innovative Learning Strategies, and Instructional Technology. These concepts are essential for understanding the integration of emerging technologies into educational and agricultural practices, particularly among younger generations.

Hypothesis 1: The Effect of the Technology Acceptance Model (TAM) on Technology Adoption

The Technology Acceptance Model (TAM), introduced [6], identifies perceived ease of use (PEOU) and perceived usefulness (PU) as key determinants of technology adoption. In the context of IoT-based fertigation, these factors are particularly important for understanding how millennials engaged in agriculture perceive and adopt this innovation. Empirical studies have consistently validated TAM as a strong predictor of technology adoption across various fields, including agriculture, where perceived ease of use and perceived usefulness significantly influence users' willingness to adopt new technologies [5], [7]. This hypothesis examines the applicability of TAM in the agricultural sector and contributes to the broader literature on technology adoption.

H1: The Technology Acceptance Model has a significant and positive effect on technology adoption.

Hypothesis 2: The Effect of Learning Quality on Technology Adoption

High-quality learning is essential for motivating users and building their confidence in adopting new technologies. Effective learning strategies, tailored content, and well-designed learning experiences are important for facilitating technology adoption, particularly in educational settings. Previous research in e-learning and digital education has emphasized the importance of well-structured learning materials, interactive platforms, and personalized learning approaches in increasing engagement and willingness to adopt new technological tools [7], [8]. This hypothesis highlights the role of educational frameworks in technology adoption, suggesting that the manner in which technology is introduced and taught can significantly influence its subsequent adoption.

H2: Learning quality has a significant and positive effect on technology adoption.

Hypotheses 3 and 4: The Moderating Role of Technology Diffusion in Technology Adoption

Diffusion, describes the process through which an innovation spreads within a social system. Factors such as the perceived attributes of an innovation, communication channels, and adopter characteristics influence the rate and extent of diffusion. Understanding the moderating role of diffusion is particularly important in contexts where social influence and network effects play a significant role. This study examines how the broader social context, as conceptualized by Innovation Diffusion Theory (IDT), influences the relationships between TAM, learning quality, and technology adoption [10].

These hypotheses investigate whether technology diffusion strengthens or weakens the effects of TAM and learning quality on technology adoption. This analysis provides insight into the interaction between individual-level factors and broader system-level factors in the process of technology adoption.

H3: Technology diffusion moderates the relationship between the Technology Acceptance Model (TAM) and technology adoption.

H4: Technology diffusion moderates the relationship between learning quality and technology adoption.

Research Stages

This study consists of several research stages, as described below:

- Literature Review
  The preliminary study involved an initial observation stage aimed at identifying and collecting the data required for the research. This stage also included a review of relevant literature and previous studies to establish the theoretical foundation and support the development of the research framework.
- Instrument Development
  At this stage, the research instruments were developed, including the preparation of a questionnaire. The questionnaire was designed based on the research objectives, theoretical framework, and relevant indicators identified from previous studies. The finalized questionnaire was then distributed to the selected respondents.
- Data Collection
  This study employed a quantitative approach using a survey method. Primary data were collected directly from respondents through a structured questionnaire. The sample was selected using a purposive sampling technique based on predetermined criteria relevant to the objectives of the study. The study population consisted of students from the Lembang and Tanjungsari State Vocational High Schools for Agricultural Development, with a total of 39 respondents. This sample size meets the minimum requirement for survey research, which is 30 respondents [11].
- Data Analysis Method
  This study employed Structural Equation Modeling (SEM) to analyze the complex relationships among variables influencing the adoption and diffusion of IoT-based fertigation technology among millennials in West Java. SEM was selected because of its ability to simultaneously examine relationships involving both observed and latent variables. The theoretical model primarily focuses on the relationships between exogenous variables (X) and endogenous variables (Y), representing students' perceptions of their competencies. The validity and reliability of the measurement model were assessed through convergent validity, discriminant validity, and composite reliability. Hypothesis testing, including the evaluation of R-squared (R^2) values and significance testing, was conducted to assess the structural (inner) model.

Data analysis was conducted using Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) approach, which is suitable for analyzing data that do not necessarily meet the assumption of multivariate normality. SEM-PLS, as developed [12], was implemented using IBM SPSS Statistics 22 and SmartPLS 3.0. SEM-PLS consists of three main components [13]:

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- Structural Model (Inner Model): The inner model describes the relationships among latent variables based on the underlying theoretical constructs. It is used to examine the hypothesized relationships between the constructs in the research model.
- Measurement Model (Outer Model): The outer model describes the relationships between latent variables and their respective indicators. It is used to assess the reliability and validity of the measurement instruments
- Weighting Scheme: The weighting scheme is a distinctive feature of SEM-PLS that determines the relationships between indicators and latent variables based on explained variance. This approach distinguishes PLS-SEM from covariance-based Structural Equation Modeling (CB-SEM), which primarily focuses on reproducing the covariance matrix.

RESULTS AND DISCUSSION

Evaluation of the Measurement Model

Convergent Validity

Convergent validity was assessed using the factor loading (FL) values. Indicators with factor loadings of 0.70 or higher were considered valid and retained, whereas indicators with loadings below 0.70 were excluded [14]. Suggested that, during the model development stage, a factor loading of 0.50 may still be considered acceptable; however, indicators with loadings below this threshold should be removed [15].

In the initial model, the indicators t_actus, t_risk, and t_compl had factor loadings below 0.50, indicating weak correlations with their respective constructs. These items were therefore removed to improve the validity of the measurement model, as low factor loadings may weaken the model and introduce measurement noise, thereby reducing the accuracy of subsequent analyses [16], [17]. Removing these indicators strengthened the structural model and improved its overall reliability and validity.

This process ensured that only indicators with adequate measurement strength were retained, resulting in a more accurate and robust model [18]. Furthermore, the refined measurement model provided a sound basis for subsequent discriminant validity analysis [19].

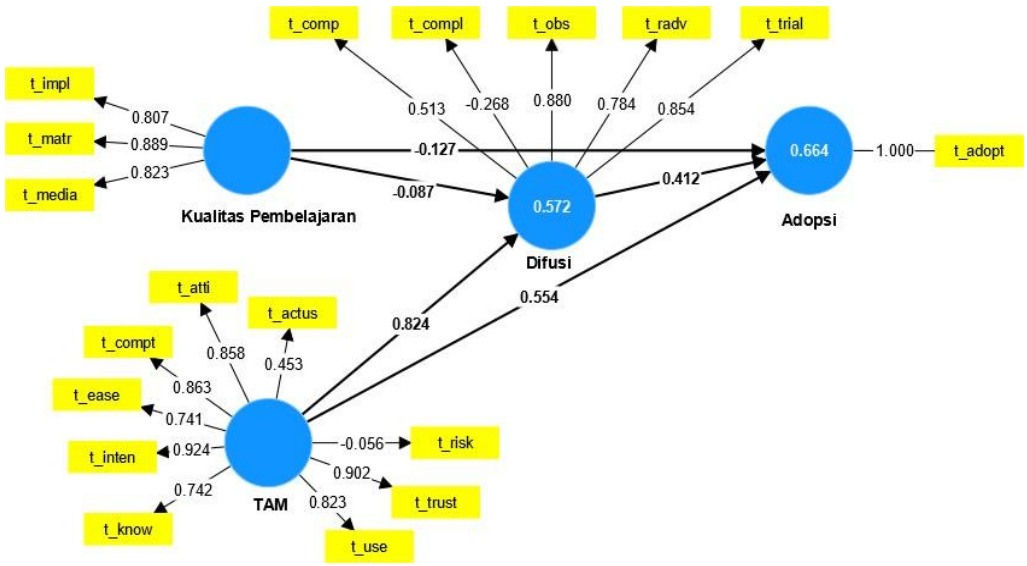


Figure 2. IoT-based fertigation technology adoption factor model prior to pruning.

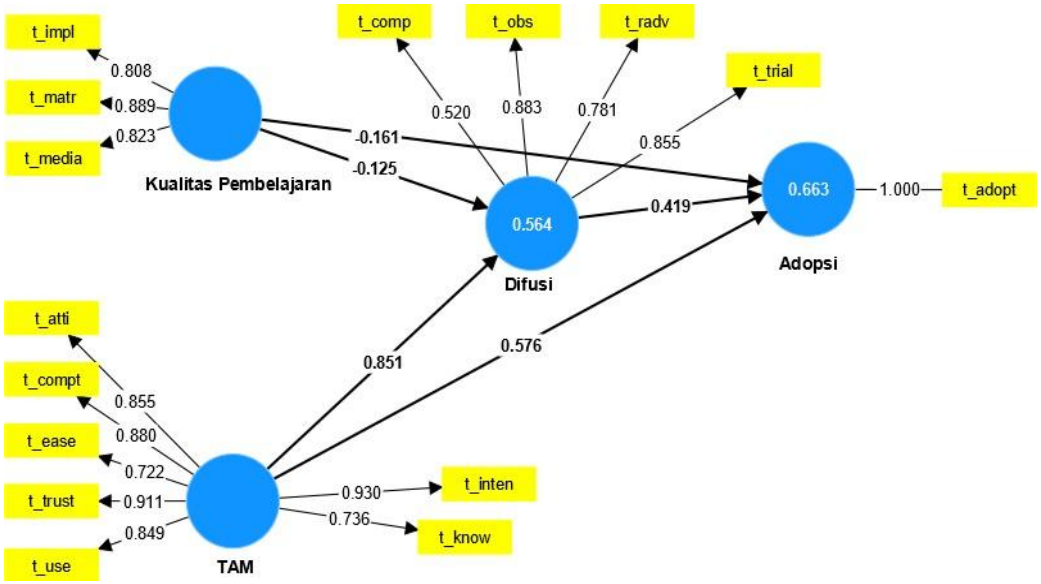


Figure 3. IoT-based fertigation technology adoption factor model after trimming.

Discriminant Validity

Discriminant validity ensures that constructs intended to be distinct are indeed separate, thereby enhancing the model's reliability [19]. This validity is assessed using Cronbach's Alpha, Average Variance Extracted (AVE), and Composite Reliability. A construct is considered reliable if Cronbach's Alpha and Composite Reliability exceed 0.7 and the AVE is above 0.5. The analysis confirms that all variables meet these criteria, thereby confirming their reliability.

Cronbach's Alpha and Composite Reliability values above 0.7 indicate strong internal consistency, while AVE values above 0.5 demonstrate that the constructs effectively explain the variance of their indicators [16]. Meeting these thresholds validates the reliability of the model [19].

Table 1. Reliability and Validity

	Cronbach Alfa	**Composite reliability (rho_a)**	**Composite reliability (rho_c)**	**Average variance extracted (AVE)**
Diffusion	0.775	0.843	0.852	0.598
quality of learning	0.794	0.819	0.878	0.707
TAM	0.931	0.940	0.945	0.712

Using the Fornell-Larcker criterion, the AVE values exceed the correlations with other constructs, confirming the model's discriminant validity. Overall, the outer model measurements meet recommended standards, supporting the use of these constructs in the broader model.

Table 2. Fornell-Larcker Test Results.

	Adoption	**Diffusion**	**Quality of learning**	**TAM**
Adoption	**1.000**			
Diffusion	0.756	**0.773**		
Quality of learning	0.555	0.576	**0.841**	
TAM	0.756	0.747	0.824	**0.844**

Structural Model Testing (Inner Model)
Inner Model Test Results

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The structural model was evaluated using the bootstrapping procedure in SmartPLS 4.0, with a significance level of 5% and a critical t-value of 1.96. Model fit and explanatory power were assessed using the R-squared (R^2) and F-squared (f^2) values. The R^2 values for technology adoption (0.663) and technology diffusion (0.564) indicate substantial and moderate explanatory power, respectively. The analysis demonstrates that the proposed model provides a strong explanatory capacity for the observed data, as indicated by the R^2 value for technology diffusion (0.564). This result indicates that 56.4% of the variance in technology diffusion is explained by the independent variables, highlighting the model's strong predictive capability in explaining the diffusion of technology. This finding is consistent with previous research emphasizing the important roles of perceived ease of use and perceived usefulness in technology adoption [20]. The relatively high R^2 value further highlights the effectiveness of the proposed model in explaining the technology diffusion process. For technology adoption, the R^2 value of 0.663 indicates that the model explains 66.3% of the variance in technology adoption, reflecting substantial explanatory power in identifying the factors that determine technology adoption. This relatively high R^2 value is consistent with the literature on the Technology Acceptance Model (TAM), which demonstrates strong predictive capability in explaining technology adoption behavior [21]. These findings further support the suitability of the proposed model for understanding the factors influencing technology adoption. Furthermore, the Q^2 value of 0.8531 confirms the model's strong predictive relevance, supporting the conclusion that TAM and learning quality significantly influence technology adoption and diffusion [22].

Table 3. R-squared value

	R-square	Adjusted R-squared
Adoption	0.663	0.625
Diffusion	0.564	0.532

The f-square values indicate that the Technology Acceptance Model (TAM) has a substantial impact on diffusion (0.531) and a moderate impact on adoption (0.206), whereas learning quality has a smaller effect on both. These metrics highlight the significant role of TAM in adoption and diffusion.

Table 4. F-Square value

	Adoption	Diffusion	Quality of learning	TAM
Diffusion	0,227 (medium)			
Quality of learning	0,024 (small)	0,012 (small)		
TAM	0,206 (medium)	0,531 (large)		

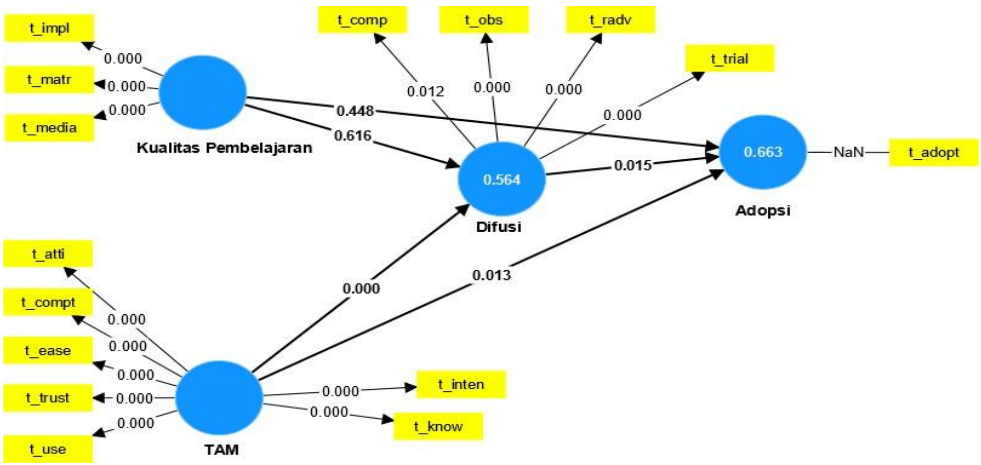


Figure 4. Inner model testing based on bootstrapping at a significance level of 0.05.

Bootstrapping results confirm that the TAM significantly influences the diffusion of fertigation technology, with the model demonstrating high validity and reliability. Most variables showed a

significant influence ($p < 0.05$); although the impact of learning quality on diffusion was less pronounced, it remained significant for the adoption of IoT-based fertigation technology among vocational high school (SMK) students.

Structural Model Equation: Factors Influencing the Diffusion and Adoption of IoT-Based Fertigation Technology

Table 5. Direct effect path coefficient value

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T-statistic (|O/STDEV|)**	**P-value**	**Significance**	**Moderating effect of status**
Diffusion -> Adoption	0.419	0.408	0.171	2.442	0.015	Significant impact	
Quality of learning -> Adoption	-0.161	-0.132	0.212	0.760	0.448	Significant impact	
TAM -> Diffusion	0.851	0.869	0.209	4.078	0.000	Significant impact	
TAM -> Adopsi	0.576	0.578	0.230	2.498	0.013	Significant impact	Direct only (without mediation)
Quality of learning -> Diffusion	-0.125	-0.110	0.250	0.502	0.616	Significant impact	No effect (no mediation)

The table 5 evaluates the significance, strength, and direction of the relationships between variables using t-statistics and p-values. Based on the coefficient values in Table 5, the structural model equation is formulated as follows:

$\eta 1$ (DIFUSI) = $0.125\xi 1$(KP) + $0.851\xi 2$(TAM) + $\zeta 1\ \eta 2$

(ADOPSI) = $0.576\eta 1$(TAM) - $0.161\xi 1$(KP) + $0.419\xi 2$(DIFUSI) + $\zeta 1$

These coefficients indicate a positive relationship between the variables, with values approaching +1 signifying a stronger positive relationship and values approaching -1 signifying a stronger negative relationship [23]. Based on the structural equation model, several key findings were obtained, as follows:

- Key Drivers of IoT-Based Fertigation Diffusion: Learning Quality and Technology Acceptance. This analysis explores the factors influencing the diffusion of IoT-based fertigation technology among agricultural vocational high school students, focusing on two key drivers: Learning Quality and the Technology Acceptance Model (TAM).
- Role of Learning Quality: The positive relationship between Learning Quality and diffusion ($\beta = 0.125$) underscores the importance of effective knowledge transfer and skill development. High-quality learning experiences enhance diffusion by:
- Enhancing Perceived Usefulness: Structured training highlights practical benefits, improving students' perception of the technology.
- Reducing Complexity: Simplifying complex concepts makes technology more approachable. [20].
- Boosting Confidence: Practical exercises build user confidence, encouraging adoption and advocacy [24].

TAM Influence: The strong positive relationship between TAM and diffusion ($\beta = 0.851$) indicates that positive perceptions of technology are crucial for widespread adoption. Key aspects of TAM include:

- Perceived Usefulness: Students are more likely to adopt technology they perceive as beneficial to their careers [6].
- Perceived Ease of Use: An intuitive interface lowers adoption barriers and encourages engagement [6].

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This study highlights the synergistic effect between Learning Quality and TAM in driving diffusion. Positive perceptions of technology, reinforced by well-designed learning experiences, lead to deeper understanding, higher acceptance, and broader dissemination. Educational strategies should focus on fostering positive perceptions and providing high-quality learning experiences to enhance technology adoption.

Identifying Determinants of Adoption: Technology Acceptance, Prior Knowledge, and Social Influence. This analysis examines the second structural equation model (η2) to identify factors influencing the adoption of IoT-based fertigation technology among students. The model highlights the roles of user perception, prior knowledge, and social influence, revealing a positive relationship between TAM and adoption (β = 0.576), a negative relationship between prior knowledge (KP) and adoption (β = -0.161), and a positive relationship between diffusion and adoption (β = 0.419).

Technology Acceptance: The Key to Adoption. The strong relationship between TAM and adoption underscores the importance of perceived usefulness and ease of use. To increase adoption:

- Highlighting Practical Benefits: Emphasizing tangible benefits such as increased efficiency and better crop yields.
- Ensuring User-Friendliness: Designing an intuitive interface and providing comprehensive training and support.

Prior Knowledge: A Double-Edged Sword. The negative relationship between prior knowledge and adoption illustrates this:

- Knowledge Inertia: Familiarity with traditional methods can lead to resistance against new technologies.
- Overconfidence Bias: Prior knowledge can lead to excessive confidence and an underestimation of the need to learn.
- Misaligned Knowledge: Existing knowledge may not align with new technologies, thereby creating barriers to adoption.

Bridging the Knowledge Gap. To address previous knowledge challenges:

- Building on Existing Knowledge: Integrating new technology with students' existing understanding.
- Addressing Misconceptions: Clarifying the benefits of new technology and overcoming resistance.
- Provide Tailored Training: Offer learning paths suited to various levels of prior knowledge.

Social Influence: Driving Adoption. The positive relationship between diffusion and adoption highlights the role of social influence:

- Facilitating Peer Learning: Encouraging the sharing of experiences among early adopters.
- Building Community: Fostering mutually supportive groups for knowledge exchange and problem-solving.
- Showcasing Success Stories: Demonstrating successful technology applications to inspire adoption.

This model reveals that while perceptions of usefulness and ease of use are crucial for adoption, addressing challenges posed by prior knowledge and leveraging social influence are equally important. A comprehensive approach incorporating effective technology design, targeted training, and a supportive community is key to maximizing the adoption of IoT-based fertigation technology.

Theoretical Implications

- Support for the Technology Acceptance Model (TAM):
  This study supports the Technology Acceptance Model (TAM) as a robust framework for explaining technology adoption. The significant direct effect of TAM underscores its relevance and predictive power, reaffirming the model's core constructs perceived ease of use and

perceived usefulness as important determinants of technology adoption [5]. These findings further validate the applicability of TAM in both academic and practical contexts.

- The Role of Learning Quality:
  Although learning quality is an important factor, the findings indicate that it does not have a significant direct effect on technology adoption. This suggests that other factors, such as organizational support and cultural alignment, may have a greater influence on adoption decisions. This finding supports extended versions of TAM that incorporate additional variables, such as social influence and facilitating conditions [26]. Practitioners should therefore consider a broader range of factors when developing strategies to enhance technology adoption [26].
- Indirect Effects and Future Research:
  The marginally significant indirect effect of TAM through technology diffusion suggests the presence of complex interactions that warrant further investigation. Future research could examine mediation and moderation mechanisms in greater depth, potentially incorporating constructs such as user satisfaction and technology–task fit. Such investigations may provide a more comprehensive understanding of the factors influencing technology adoption [25].

Practical Implications

- Designing User-Friendly Technologies:
  The findings highlight the importance of developing technologies that are easy to use and perceived as valuable by users. Emphasizing usability and practical benefits can significantly enhance technology adoption, as demonstrated by the strong direct effect of TAM. Technology developers and designers should therefore focus on creating intuitive, accessible, and value-adding solutions to encourage adoption.
- Going Beyond Learning Quality:
  Organizations should recognize that, although learning quality is important, it may not be sufficient on its own to drive technology adoption. Adoption strategies should extend beyond training and learning activities to address broader organizational and contextual factors.
- Strengthening Organizational Support:
  Emphasizing organizational support, fostering a culture of innovation, and ensuring meaningful user integration into the technology ecosystem may represent more effective strategies for promoting technology adoption [6]. A holistic approach to technology adoption can facilitate more successful and sustainable technology implementation.

Overall, this study provides empirical support for the predictive strength of TAM in explaining technology adoption while highlighting the limited yet potentially important role of learning quality. Although some relationships were not statistically significant, the findings provide a strong foundation for future research and offer practical guidance for improving technology adoption in organizational and educational settings. These insights contribute to both the theoretical understanding and practical application of technology adoption strategies.

CONCLUSION

The results of this study confirm the significant effects of both the Technology Acceptance Model (TAM) and perceived learning quality on technology adoption and diffusion. TAM demonstrates a strong positive relationship with technology diffusion ($\beta = 0.851$) and technology adoption ($\beta = 0.576$). Meanwhile, perceived learning quality has a direct and positive effect on technology diffusion ($\beta = 0.125$), while its direct effect on technology adoption is negative ($\beta = -0.161$). However, perceived learning quality has a positive indirect effect on technology adoption through technology diffusion ($\beta = 0.356$). This study supports the Technology Acceptance Model (TAM) as a robust framework for explaining technology adoption. The significant direct effect of TAM underscores its relevance and predictive power, reaffirming the model's core constructs—perceived ease of use and perceived usefulness—as important determinants of technology adoption. Although the quality of learning is important, it does not directly influence implementation. This indicates that other factors, such as organizational support and cultural alignment, may have a greater impact. Practitioners should consider a broader range of factors to enhance technology

implementation. The marginally significant indirect effect of TAM via DIFFUSION indicates a complex interaction that warrants further investigation. Future research could explore mediation and moderation mechanisms in greater depth, potentially integrating constructs such as user satisfaction and technology fit. These results underscore the importance of positive perceptions of technology and effective learning experiences in driving the successful adoption of smart agricultural innovations among future agricultural professionals.

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