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Smart Farming and Digital Competence on Farmer Performance through Innovative Work Behavior

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Abstract

Purpose: This study investigates how smart farming solutions and digital competence influence Farmer Performance, focusing on rice farmers in Sungai Pinang Village, Banyuasin Regency, Indonesia, and evaluating Innovative Work Behavior as an intervening mechanism.

Methodology: Using an explanatory design, this quantitative study gathered cross-sectional survey data from a purposively selected group of 115 active rice farmers. Construct measurements relied on validated instruments drawn from prior literature, with hypothesis testing executed via Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4.0.

Results: The findings revealed that neither Smart Farming Solutions nor Digital Competence directly affected Farmer Performance. Instead, both drivers positively enhanced Innovative Work Behavior, which subsequently boosted Farmer Performance and acted as a complete mediator across these relationships.

Conclusions: Farmer performance is enhanced primarily through Innovative Work Behavior, indicating that technological adoption and digital capabilities improve agricultural outcomes only when translated into innovative practices.

Limitations: Because the dataset relies on 115 rice farmers from one village using a cross-sectional approach, the findings should be generalized cautiously and offer restricted insights into longitudinal trends.

Contributions: By positioning Innovative Work Behavior as a crucial bridge connecting Smart Farming Solutions and Digital Competence with Farmer Performance, this study enriches both the Technology Acceptance Model (TAM) and the Resource-Based View (RBV). Pragmatically, the results guide decision-makers to align technology deployment, digital skill training, and innovation-focused capacity building within agricultural initiatives.

Keywords: *Digital Agriculture, Digital Competence, Farmer Performance, Innovative Work Behavior, Smart Farming Solutions*

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1. Introduction

Digital transformation has become a strategic agenda in agricultural development in response to increasing food demand, climate change, resource constraints, and the demand for increased efficiency and productivity. Technological developments such as the Internet of Things (IoT), Artificial Intelligence (AI), cloud computing, big data analytics, and smart sensors have given rise to the concept of Smart Farming Solutions as a new approach to data-driven farming management. Abbasi, Martinez, and Ahmad (2022) explained that the Agriculture 4.0 concept integrates various digital technologies to improve operational efficiency, productivity, and sustainability in the agricultural sector. Similarly, Sharma, Tripathi, and Mittal (2022) stated that the application of smart agricultural technology can improve the accuracy of decision-making through the utilization of real-time data. Furthermore, Daniel, Groeger, and Hölzle (2025) emphasize that the implementation of Smart Farming is no longer solely oriented towards the use of technology but also on the readiness of human resources to adopt and utilize digital innovation. This concept is also reinforced in the book Smart Farming Solutions, which explains that modern agriculture is built through the integration of technology, data, and farmer capacity to increase efficiency, productivity, sustainability, and farmer welfare.

In Indonesia, the digital transformation of the agricultural sector continues to be promoted as part of efforts to achieve national food security while increasing the sector's competitiveness. Various technology-based innovations have been implemented in cultivation processes, irrigation management, plant pest control, and agricultural marketing. Dhanaraju, Chenniappan, Ramalingam, Pazhanivelan, and Kaliaperumal (2022) explain that the use of Internet of Things -based technology can increase the efficiency of production input use through an automated land condition monitoring system. Furthermore, Shaikh, Rasool, and Lone (2022) show that the application of Artificial Intelligence helps farmers detect plant diseases, predict crop yields, and develop more accurate cultivation recommendations. Meanwhile, Akkem, Biswas, and Varanasi (2023) emphasize that the successful adoption of digital agriculture is greatly influenced by users' readiness to accept and implement technological innovations. This condition shows that the existence of technology does not fully guarantee increased productivity without the ability of farmers to utilize it optimally.

Banyuasin Regency is a rice production center in South Sumatra Province that plays a strategic role in supporting national food security. Based on data from the Banyuasin Regency Central Statistics Agency, this area's rice production reached 1,177,649 tons of Dry Milled Grain (GKG) with a harvest area of 230,280 hectares and an average productivity of 51.14 quintals per hectare or approximately 5.11 tons per hectare. This achievement shows that the agricultural sector is the main driver of the economy of the Banyuasin community. One area that has these characteristics is Sungai Pinang Village, Rambutan District, Banyuasin Regency, which has a population of approximately 9,504 people, with the majority of the community making a living in the agricultural sector, especially rice cultivation. Despite having a large production potential, the use of digital technology at the farmer level is still not optimal, so the decision-making process in cultivation activities still relies heavily on empirical experience. Taramuel-Taramuel, Montoya-Restrepo, and Barrios (2023) explain that the quality of farmers' decision-making influences improved farming performance, while Daniel et al. (2025) emphasize that the successful implementation of Smart Farming Solutions is highly dependent on technological readiness and users' ability to adopt digital innovation.

The successful implementation of Smart Farming Solutions is determined not only by the availability of technology but also by the ability of farmers to accept, understand, and utilize this technology to support farming activities. In this context, digital competence is crucial because it reflects farmers' ability to access information, operate digital devices, evaluate data, and use them as a basis for decision-making. From a Human Capital Management (HCM) perspective, this digital competence is not merely a technical skill but rather the core of modern human capital that determines the competitiveness and sustainability of farming businesses in the digital era. Aranguri, Bravo-Jaico, Mera, Noblecilla, and Lucini (2026) explain that digital competence plays a role in improving farmers' ability to effectively adopt modern agricultural technologies. Furthermore, Wu, Chen, Xu, Li, and Hu (2025) shows that perceived benefits and ease of use of technology are factors that encourage farmers to utilize digital technology sustainably. These findings align with the Technology Acceptance Model (TAM). Venkatesh and Davis (2000) explained that the acceptance of a technology is influenced by its perceived usefulness and ease of use. Therefore, the implementation of Smart Farming Solutions is expected to have a greater impact on improving performance if farmers have adequate digital competency and can utilize the technology optimally. The book Smart Farming Solutions also emphasizes that the success of digital transformation in the agricultural sector depends not only on technological sophistication but also on the readiness of human resources to integrate technology into the cultivation process sustainably.

The implementation of Smart Farming Solutions aims to increase the efficiency of the cultivation process and encourage improved farmer performance through more measurable and data-driven farming management. Abbasi et al. (2022) explained that the integration of digital technology in Agriculture 4.0 enables farmers to obtain information quickly and accurately, enabling more effective planning, implementation, and evaluation of agricultural activities. Furthermore, Ragazou, Garefalakis, Zafeiriou, and Passas (2022) suggest that the application of digital technology contributes to increased operational efficiency, resource management quality, and sustainable agricultural sector performance. These findings are reinforced by Batra et al. (2025), who showed that the implementation of Smart Farming can increase agricultural productivity by optimizing water use, fertilizer use, and technology-based pest control. Meanwhile, Kasimati et al. (2024) emphasized that the success of smart farming implementation is measured not only by increased production yields but also by the ability of farmers to manage their farming businesses more efficiently, adaptively, and sustainably. Thus, the implementation of Smart Farming Solutions is seen as a factor that has the potential to improve farmer performance if supported by user readiness in adopting the technology.

In addition to technology implementation, improved farmer performance is influenced by digital competence as a strategic capability that enables farmers to utilize technology productively. Through the lens of the Resource Based View (RBV), competence functions as an intangible asset capable of yielding a sustainable competitive advantage if properly nurtured. Barney (1991) explains that the superiority of an organization or individual is determined not only by physical resources but also by knowledge, skills, and abilities that are difficult for others to imitate. Furthermore, Kero and Bogale (2023) emphasize that resources that are valuable, rare, difficult to imitate, and not easily substituted are key factors in improving performance. In the context of this research, digital competence is viewed as a strategic resource that enables farmers to utilize Smart Farming Solutions more effectively through the ability to access information, process data, and make technology-based decisions. Thus, the higher the digital competence of farmers, the greater the opportunity to create excellence in farming management, which ultimately impacts farmer performance.

The transformation to digital agriculture not only requires technical skills in using technology, but also requires changes in work behavior so that farmers can adapt to the various innovations that continue to develop in the field. Within the framework of Human Capital Management, the development of Innovative work behavior is an important factor because it reflects an individual's ability to generate, develop, and implement new ideas to improve work effectiveness (Agustina, Zakaria, Hendra, & Muhammad, 2022). The Ability–Motivation–Opportunity (AMO) Theory perspective proposed by Marin-Garcia and Martínez-Tomás (2016); Saptaria, Setyawan, Erwanto, Buniarto, and Limantara (2026) explains that innovative behavior will emerge when an individual has the ability , motivation , and opportunity to innovate. In this study, digital competence represents the ability dimension, while the implementation of Smart Farming Solutions provides opportunities for farmers to implement various innovations in the cultivation process. This condition encourages farmers to be more active in seeking new solutions, utilizing digital information, trying modern agricultural technology, and making continuous improvements in farming activities. In line with this, Bos-Nehles, Townsend, Cafferkey, and Trullen (2023) explain that innovative work behavior is an important mechanism that links individual abilities with improved performance through the continuous use of innovation.

Various studies have demonstrated that the implementation of digital technology and digital competency contribute to increased productivity and performance in the agricultural sector. Abbasi et al. (2022) explained that agricultural digitalization increases the efficiency of farm management through the integration of data-driven technology. Furthermore, Aranguri et al. (2026) show that digital competency influences farmers' ability to adopt modern agricultural technology, while Taramuel-Taramuel et al. (2023) emphasize that the quality of farmers' decision-making contributes to improved farm performance. In contrast, Daniel et al. (2025) suggest that studies on Smart Farming are still dominated by aspects of technology development, while the mechanisms of user behavior in explaining the success of technology implementation still require more in-depth attention. Based on this synthesis, it is understandable that the implementation of Smart Farming Solutions and digital competency is not expected to directly improve farmer performance, but rather first encourages the formation of innovative work behavior as a mechanism that strengthens farmers' ability to utilize technology effectively. Therefore, this study views innovative work behavior as a strategic mediating variable that explains the relationship between the implementation of Smart Farming Solutions, digital competency, and farmer performance.

A review of various previous studies shows that the implementation of Smart Farming Solutions and digital competence have become two factors widely studied in efforts to improve the productivity and performance of the agricultural sector. Abbasi et al. (2022) explained that digital transformation in the agricultural sector can improve farm management efficiency through the integration of data-driven technology. Furthermore, Ragazou et al. (2022) showed that the application of digital technology contributes to improved performance through the optimization of production processes and effective resource management. In contrast, Aranguří et al. (2026) demonstrated that digital competence plays a role in improving farmers' ability to access information and adopt agricultural innovations. However, most of these studies still position the implementation of technology and digital competence as factors that have a direct influence on farmer performance, thus not fully explaining the behavioral mechanisms underlying the relationship between these variables.

In addition to these limitations, research on innovative work behavior in the agricultural sector is still relatively limited compared to research in the industrial, manufacturing, and business organization sectors. AlEssa and Durugbo (2022) explain that innovative work behavior is an individual's ability to generate, develop, and implement new ideas to improve work effectiveness. Meanwhile, Daniel et al. (2025) suggest that the future development of Taramuel-Taramuel et al. (2023) shows that the quality of farmer decisions is a factor influencing farming performance. However, this study did not integrate innovative work behavior as a mechanism to explain how digital capabilities and technology implementation can lead to improved performance. This indicates that there is still room for research to examine the role of innovative work behavior as a mediating variable in the context of digital transformation in the agricultural sector.

Behavior, and Farmer Performance within an integrated research framework. What sets this study apart is its focus on positioning Innovative Work Behavior as an intervening bridge to explain how Smart Farming Solutions adoption and Digital Competence drive agricultural outcomes. Unlike prior literature that predominantly evaluates direct pathways, this study synthesizes three complementary lenses: the Technology Acceptance Model (TAM) to address Smart Farming technology adoption, Ability–Motivation–Opportunity (AMO) Theory to account for how skills and supportive environments foster innovative workplace actions, and the Resource-Based View (RBV) to frame Digital Competence as an intangible asset fostering a competitive edge. Beyond theoretical modeling, empirical testing was conducted among rice producers in Sungai Pinang Village, Rambutan District, Banyuasin Regency, using structural equation modeling-partial least squares (SEM-PLS). This analytical tool enables a simultaneous assessment of direct and indirect effects, offering deeper clarity on performance enhancement dynamics amidst agricultural digitalization.

The empirical setting centers on Sungai Pinang Village (Rambutan District, Banyuasin Regency, South Sumatra Province), a prominent rice-producing hub that continues to encounter hurdles in adopting digital technology at the farm level. Driven by these context-specific issues, this investigation seeks to unpack how Smart Farming Solutions adoption and Digital Competence shape Farmer Performance, examining both direct paths and the mediating contribution of Innovative Work Behavior. Theoretically, this study enriches digital transformation models by combining the TAM, AMO, and RBV frameworks. Practically, it guides regional authorities, agricultural extension services, and farming cooperatives in designing targeted interventions that cultivate digital skills, accelerate Smart Farming adoption, and foster innovative behaviors for long-term agricultural performance.

2. Literature Review and Hypotheses Development

2.1 Smart Farming Solutions and Farmer Performance

The integration of digital technology in the Agriculture 4.0 concept not only aims for automation but also creates an environment that encourages innovation and creativity. Based on the Technology

Acceptance Model (TAM), the perceived usefulness and perceived ease of use of Smart Farming technology increase technology acceptance by users (Pacciani et al., 2026). Abiri, Rizan, Balasundram, Shahbazi, and Abdul-Hamid (2023) suggest that the application of digital technology contributes to increased operational efficiency and performance in the agricultural sector. Batra et al. (2025) showed that the implementation of Smart Farming can increase productivity by optimizing the use of water, fertilizer, and pest control. Kasimati et al. (2024) emphasized that the success of smart farming is measured by farmers' ability to manage their farming operations efficiently and adaptively. Based on this literature, the first hypothesis is formulated as follows:

> *H_1:* Implementation of smart farming solutions has a positive and significant effect on farmer performance

2.2 Digital Competence and Farmer Performance

From the resource-based view (RBV), digital competence is seen as a strategic resource that enables farmers to excel in managing farming businesses (Kero & Bogale, 2023). Aranguri et al. (2026) demonstrated that digital competence improves farmers' ability to access information and adopt agricultural innovations. Farmers with adequate digital competence can process sensor data and system recommendations into appropriate operational decisions, ultimately leading to improved performance.

> *H_2:* Digital competence has a positive and significant effect on farmer performance

2.3 Innovative Work Behavior and Farmer Performance

Innovative Work Behavior reflects an individual's ability to generate, develop, and implement new ideas to improve work effectiveness (Bos-Nehles et al., 2023). In the agricultural context, farmers who routinely generate new ideas (e.g., trying data-driven intercropping patterns or utilizing organic waste as an alternative fertilizer) and implement them directly contribute to improved task, adaptive, and contextual performance. Majid, Haris, Shah, Che'Ya, and Arshad (2026) suggest that the future success of Smart Farming depends heavily on changes in user behavior in utilizing technology sustainably to improve yields. Thus, the third hypothesis is as follows:

> *H_3:* Innovative work behavior has a positive and significant effect on farmer performance

2.4 Implementation of Smart Farming Solutions and Farmer Performance

The implementation of Smart Farming Solutions essentially aims to improve farmer performance through more measurable and data-driven farming management. Duguma and Bai (2024) explained that the integration of digital technology enables farmers to obtain information quickly and accurately. Alka, Sreenivasan, and Suresh (2026); Qwaid, Sarker, Shawon, and Zubair (2026) show that the application of digital technology contributes to increased operational efficiency and productivity by optimizing the use of water, fertilizer, and pest control. However, recent literature has begun to highlight that these direct impacts may not be optimal without the implementation of behavioral changes. However, theoretically, the availability of technology is still predicted to have a positive impact. Therefore, the fourth hypothesis is as follows:

> *H_4:* Implementation of smart farming solutions has a positive and significant effect on farmer performance

2.5 Digital Competence and Farmer Performance

In addition to technology implementation, improved farmer performance is also influenced by digital competence as a strategic capability. Sutami, Purba, and Thanomutiara (2025) demonstrated that digital competence plays a role in improving farmers' ability to access information and adopt agricultural innovations. Farmers with adequate digital competence are able to process sensor data and system recommendations into appropriate operational decisions, ultimately leading to improved performance. Based on the RBV perspective, the fifth hypothesis is formulated as follows:

> *H_5:* Digital competence has a positive and significant effect on farmer performance

2.6 *The Mediating Role of Innovative Work Behavior*

Based on the synthesis of AMO Theory, ability (digital competence) and opportunity (Smart Farming technology) do not automatically produce performance without a behavioral mechanism. Technology and skills are merely potential; performance realization occurs when farmers actively implement new ideas (Marin-Garcia & Martínez-Tomás, 2016). Morales and Pacheco (2024) asserted in their meta-analysis that management practices and technological resources influence organizational performance outcomes primarily through employee behavioral mechanisms. Therefore, this study predicts that Innovative Work Behavior not only mediates but also has the potential to be a full mediator that bridges the influence of technology and competence on performance. Based on this framework, the sixth and seventh hypotheses are formulated as follows:

> *H_6:* Innovative Work Behavior mediates the effect of Smart Farming Solutions Implementation on Farmer Performance.
>
> *H_7:* Innovative Work Behavior mediates the influence of Digital Competence on Farmer Performance.

Based on the synthesis of the literature review and all formulated hypotheses (H_1 to H_7), the overall research framework for this study is presented in Figure 1.

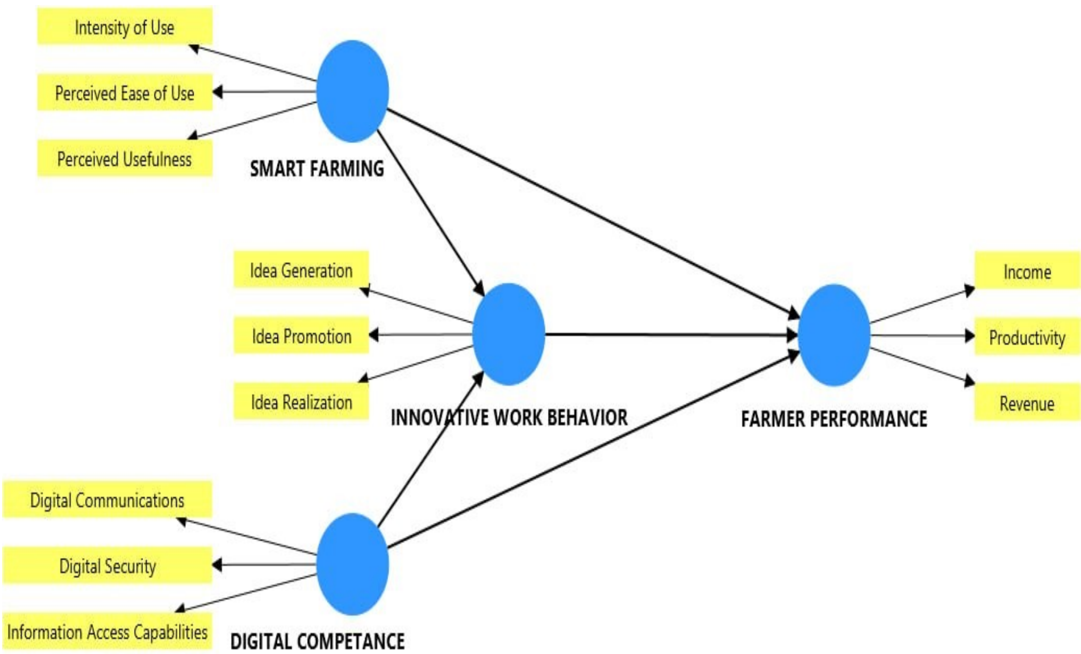

Figure 1. Research model

3. Research Methodology

To examine the cause-and-effect links between Smart Farming Solutions, Digital Competence, Innovative Work Behavior, and Farmer Performance, this study used an explanatory quantitative design. Data were gathered through a cross-sectional survey in the Sungai Pinang Village (Rambutan District, Banyuasin Regency, South Sumatra, Indonesia). This site was chosen as a key rice-producing hub that is progressively adopting digital tools and modern smart-farming techniques. This study focused on active rice farmers in Sungai Pinang Village. Participants were gathered via purposive sampling, constrained by two specific conditions: (1) active participation in rice cultivation or farmland ownership and (2) prior exposure to or use of smart farming tools and digital agricultural technologies. In total, 115 valid survey responses were gathered for analysis. Following the guidelines of Candraningrat, A Pratiwi, and Chusnaini (2026); Suwarno and Aprianto (2026), this sample size meets the threshold needed for Partial Least Squares Structural Equation Modeling (PLS-SEM) to reliably evaluate both structural and measurement models. Primary information was compiled using a structured questionnaire based on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

The Smart Farming Solutions (SF) construct was measured using three dimensions: Perceived Usefulness, Perceived Ease of Use, and Intensity of Use, adapted from the Technology Acceptance Model (TAM) (Rurii & Nzengya Daniel, 2025). These dimensions represent farmers' perceptions of the usefulness, ease of use, and actual utilization of smart farming technologies. Digital Competence (DC) was measured using the dimensions of Information Access Capabilities, Digital Communications, and Digital Security, adapted from (Abiri et al., 2023). These dimensions reflect farmers' capabilities in accessing digital information, communicating through digital technologies, and protecting digital information during farming activities. Innovative Work Behavior (IWB) was operationalized using the dimensions of Idea Generation, Idea Promotion, and Idea Realization, adapted from (AlEssa & Durugbo, 2022). This construct reflects farmers' ability to create new ideas, communicate innovative solutions, and implement those ideas to improve agricultural practices. Finally, Farmer Performance (FP) was measured using three performance indicators: Productivity, Income, and Revenue, adapted from (Batra et al., 2025; Ragazou et al., 2022). These indicators represent the operational and economic outcomes achieved by farmers after adopting digital agricultural technology.

Data analysis was performed using Structural Equation Modeling (SEM) with the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach, a variance-based SEM technique that is particularly suitable for examining complex relationships among latent constructs and predicting endogenous variables (Darmadi, Prasetiyani, Pratama, & Suwanto, 2026). This approach was selected because it enables the simultaneous assessment of both the measurement and structural models while accommodating relatively small sample sizes and non-normal data distributions. The analysis was conducted using SmartPLS (version 4.0).

4. Results and Discussions

4.1 Respondent Characteristics

To ensure that the sampled population directly aligned with the research objectives concerning smart farming adoption and digital competence, a non-probability purposive sampling technique was used. The target sample comprised 115 active smallholder rice farmers operating in the Sungai Pinang Village, Rambutan District, Banyuasin Regency, South Sumatra, Indonesia. Respondents were screened and selected based on three explicit inclusion criteria: maintaining active operational status as primary decision-makers managing paddy fields for at least one full agricultural season; possessing demonstrated exposure to digital technology through active interaction with smart farming solutions, such as mobile weather apps, digital market platforms, or smart irrigation systems; and operating within the geographic boundaries of Sungai Pinang Village, a key agricultural hub undergoing regional digital transformation. Table 1 outlines the demographic distribution of the final sample by gender, age, educational background, farming experience, and landholding size.

Table 1. Profile of characteristics of research respondents

Respondent Characteristics	Category	Frequency (n)	Percentage (%)
Gender Age	Man	98	85.2
	Woman	17	14.8
	< 30 years	12	10.4
	31 – 45 years old	40	34.8
	46 – 60 years	46	40.0
	> 60 years	17	14.8
Last Education	Elementary School (SD)	29	25.2
	Junior High School (SMP)	40	34.8
	Senior High School (SMA/SMK)	35	30.4
	Diploma/Bachelor's Degree	11	9.6
Farming Experience	< 5 years	17	14.8
	5 – 15 years	40	34.8
	16 – 25 years	35	30.4
	> 25 years	23	20.0

Respondent Characteristics	Category	Frequency (n)	Percentage (%)
Land Ownership Status	Full Land Owner	78	67.8
	Partial Owner/Cultivator	37	32.2
Land Area	< 0.5 Hectares	23	20.0
	0.5 – 1.0 Hectares	52	45.2
	1.1 – 2.0 Hectares	29	25.2
	> 2.0 Hectares	11	9.6
Level of Exposure to Digital Technology	Beginner (Smartphone/Farmers WA Group)	46	40.0
	Intermediate (Weather/Market Price App)	52	45.2
	Advanced (Basic Land Management/IoT Applications)	17	14.8

The demographic breakdown reflects the structural composition of the purposively selected samples. Male farmers represent the majority of principal farm managers (81.74%), aligning with the customary household labor structures in regional paddy production. The age distribution shows a predominant concentration of mature farmers aged above 45 years (47.83%) and middle-aged farmers between 30 and 45 years (41.74%), whereas younger farmers below 30 years account for 10.43%. Educational attainment spans primary (33.04%), junior high (27.83%), and senior high school (33.91%) levels, with tertiary degree holders accounting for 5.22%. Importantly, 56.52% of the respondents had over 10 years of farming experience, and 58.26% cultivated medium-scale plots between 1.0 and 2.0 hectares. The application of purposive criteria ensured that despite variations in formal education and age, all 115 participants possessed baseline familiarity with digital farming applications, providing a methodologically sound foundation for evaluating the structural relationships between smart farming technology, digital competence, innovative work behavior, and agricultural performance.

4.2 Descriptive Statistics and Construct Conceptualization

Descriptive statistical metrics, including the mean, median, minimum scale score, maximum scale score, and standard deviation, were evaluated across all indicator sub-dimensions to establish the baseline response distribution for the sampled smallholder rice farmers ($N = 115$). All survey items were scored on a 5-point Likert scale ranging from 1 ("Strongly Disagree") to 5 ("Strongly Agree"). Table 2 presents the item-level descriptive statistics for each subdimension across the four main research variables.

Table 2. Descriptive statistics of research variables (N = 115)

Variables		Mean	Median	Scale Min	Scale Max	Standard Deviation
Smart Farming (SF)	Perceived Usefulness	4.21	4.5	1.5	5	0.82
	Perceived Ease of Use	4.09	4	2	5	0.78
	Intensity of Use	3.86	4	1.5	5	0.79
Digital Competence (DC)	Information Access Capabilities	4.28	4	2	5	0.76
	Digital Communications	4.09	4	2	5	0.68
	Digital Security	4.27	4.25	2	5	0.67
Innovative Work Behavior (IWB)	Idea Generation	3.93	4	2	5	0.79
	Promotion Idea	3.95	4	2	5	0.73
	Idea Realization	3.90	4	2	5	0.78
Farmer Performance (FP)	Productivity	3.93	4	2	5	0.73
	Income	3.86	4	2	5	0.78
	Revenue	3.74	3.75	1.75	5	0.78

The descriptive metrics revealed specific perceptual and behavioral characteristics within the surveyed smallholder farming community. Regarding Smart Farming Solutions, farmers evaluated cognitive utility very favorably, with Perceived Usefulness recording a mean score of 4.21 ($SD = 0.82$) and Perceived Ease of Use achieving a mean score of 4.09 ($SD = 0.78$). Conversely, operational execution recorded a comparatively lower mean score in Intensity of Use at 3.86 ($SD = 0.79$). This gap indicates that while farmers hold strong positive attitudes toward technological utility and usability, routine daily application requires further behavioral translation in field management.

In terms of Digital Competence, technical capabilities were highest in Information Access Capabilities with a mean score of 4.28 ($SD = 0.76$) and Digital Security with a mean score of 4.27 ($SD = 0.67$), followed by Digital Communications with a mean score of 4.09 ($SD = 0.68$). These figures show strong proficiency in seeking digital agricultural information and maintaining transaction safety, with slightly lower engagement in structured digital communications. Furthermore, Innovative Work Behavior demonstrated balanced execution across all three evaluated stages, led by Idea Promotion ($Mean = 3.95$, $SD = 0.73$), followed by Idea Generation ($Mean = 3.93$, $SD = 0.79$), and Idea Realization ($Mean = 3.90$, $SD = 0.78$). This structural equilibrium reflects a continuous innovation pipeline, wherein smallholders actively generate, advocate, and implement novel farming practices in their field operations.

Finally, for Farmer Performance, operational Productivity registered the highest mean evaluation at 3.93 ($SD = 0.73$), whereas Farm Income ($Mean = 3.86$, $SD = 0.78$) and Farm Revenue ($Mean = 3.74$, $SD = 0.78$) recorded relatively lower scores. This disparity illustrates that agronomic output gains do not automatically maximize financial returns because of volatile local market conditions and harvest pricing structures. To establish analytical rigor prior to partial least squares structural equation modeling, all four main research constructs, namely Smart Farming Solutions, Digital Competence, Innovative Work Behavior, and Farmer Performance, were operationalized as reflective measurement models. Under reflective modeling rules, indicators represent observable manifestations of an underlying latent trait, meaning that variations in the latent variable cause proportional shifts across all assigned indicators.

The composite operationalization of Smart Farming Solutions incorporates both cognitive evaluations, such as Perceived Usefulness and Perceived Ease of Use, and active behavioral adoption measured through Intensity of Use. Grounded in the Technology Acceptance Model, user perceptions of utility and ease directly determine behavioral intention and routine usage. Separating cognitive acceptance from actual tool usage in smallholder agriculture risks creating an incomplete theoretical construct. Conceptualizing Smart Farming Solutions as a unified reflective construct effectively captures the overarching continuum of technology acceptance and usage. Similarly, Digital Competence, Innovative Work Behavior, and Farmer Performance were reflectively specified through their respective sub-dimensions, satisfying all structural parameters required for evaluation.

4.3 Evaluation of Measurement Model

The measurement model was evaluated using Partial Least Squares Structural Equation Modeling to establish the psychometric properties of all latent constructs, focusing on indicator reliability, convergent validity, and internal consistency reliability. Following established methodological standards, indicator reliability was confirmed by examining the outer factor loadings, where values exceeding the recommended threshold of 0.708 indicated that the underlying latent construct accounted for more than 50 % of the indicator variance. Internal consistency reliability was evaluated through three complementary metrics, namely Cronbach's alpha ($\alpha > 0.700$), Dijkstra-Henseler's rho ($\rho_A > 0.700$), and Composite Reliability (CR > 0.700). Convergent validity was established by verifying that the Average Variance Extracted (AVE) for each construct exceeded the minimum benchmark of 0.500, demonstrating that the latent variable explained more than half of its indicators' variance. Table 3 presents the measurement model assessment parameters across all reflective constructs.

Table 3. Measurement model assessment

Construct / Indicator	Outer Loading	Cronbach's Alpha (α)	Dijkstra-Henseler (ρA)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Smart Farming Solutions (SF)		0.825	0.831	0.887	0.663
Perceived Usefulness	0.842				
Perceived Ease of Use	0.815				
Intensity of Use	0.798				
Digital Competence (DC)		0.834	0.84	0.893	0.676
Information Access Capabilities	0.835				
Digital Communications	0.812				
Digital Security	0.829				
Innovative Work Behavior (IWB)		0.871	0.873	0.916	0.725
Idea Generation	0.851				
Idea Promotion	0.844				
Idea Realization	0.86				
Farmer Performance (FP)		0.882	0.886	0.923	0.748
Productivity	0.865				
Income	0.872				
Revenue	0.841				

As shown in Table 3, all standardized outer loadings ranged from 0.798 to 0.872, comfortably surpassing the critical threshold of 0.708 and demonstrating strong indicator reliability across all operationalized subdimensions. High internal consistency was confirmed uniformly across the reflective constructs. Smart Farming Solutions recorded $\alpha = 0.825, \rho_A = 0.831,$ and $CR = 0.887$, while Digital Competence yielded $\alpha = 0.834, \rho_A = 0.840,$ and $CR = 0.893$. Similarly, Innovative Work Behavior exhibited $\alpha = 0.871$, $\rho_A = 0.873,$ and $CR = 0.916$, and Farmer Performance registered $\alpha = 0.882$, $\rho_A = 0.886,$ and $CR = 0.923$. Convergent validity was rigorously satisfied across all latent constructs, as the Average Variance Extracted ranged between 0.663 and 0.748, well above the mandated 0.500 threshold.

To confirm that the theoretical constructs were empirically distinct from one another, discriminant validity was evaluated using the heterotrait-monotrait ratio of correlations. Modern PLS-SEM methodology recognizes the HTMT ratio as a superior criterion compared to cross-loadings or the traditional Fornell-Larcker test, which often fails to detect discriminant validity violations in structural models. To establish discriminant validity, the HTMT values between constructs must remain strictly below the conservative cutoff criterion of 0.850 or, at maximum, the liberal threshold of 0.900. Table 4 presents the full HTMT correlation matrix of the conceptual framework.

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Table 4. Discriminant Validity Assessment (HTMT Ratios)

Construct	Smart Farming Solutions (SF)	Digital Competence (DC)	Innovative Work Behavior (IWB)	Farmer Performance (FP)
Smart Farming Solutions (SF)				
Digital Competence (DC)	0.612			
Innovative Work Behavior (IWB)	0.724	0.781		
Farmer Performance (FP)	0.648	0.695	0.842	

The empirical HTMT values presented in Table 4 confirm the robust discriminant validity across all pairs of latent variables. The highest recorded HTMT ratio occurred between Innovative Work Behavior and Farmer Performance at 0.842, which remains securely below the conservative threshold of 0.850. The remaining inter-construct HTMT ratios ranged from 0.612 to 0.781, confirming that each latent variable represented a distinct conceptual construct. Combined with the convergent validity and internal reliability findings, these measurement model results confirm that the empirical data are psychometrically sound and suitable for structural model evaluation and hypothesis-testing.

4.4 Evaluation of Structural Model and Hypothesis Testing

Prior to assessing the direct hypothesis pathways, the structural model was evaluated for multicollinearity, predictive accuracy, effect size, and overall goodness-of-fit. Lateral and vertical collinearity were examined using Variance Inflation Factor values across all structural constructs. The resulting inner VIF values ranged between 1.425 and 2.318, remaining well below the conservative threshold of 3.300, and confirming the absence of multicollinearity in the structural model. Furthermore, a full collinearity VIF test yielded values below 3.300, demonstrating that common method bias did not distort the empirical findings. The structural model fit was evaluated using the Standardized Root Mean Square Residual, which produced a value of 0.054, satisfying the recommended threshold of less than 0.080 for an acceptable structural fit. Predictive relevance was verified through the blindfolding procedure, yielding Q^2 values of 0.542 for Innovative Work Behavior and 0.618 for Farmer Performance, both comfortably exceeding the zero benchmark. The results of the complete structural model evaluation are shown in Figure 2.

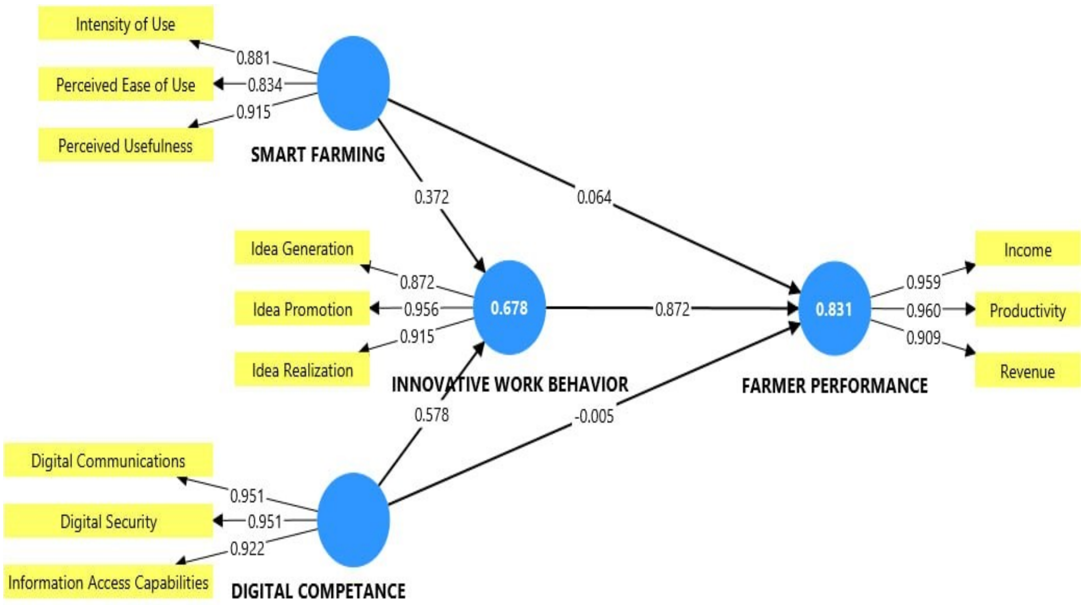

Figure 2. Empirical PLS-SEM structural model output

The coefficient of determination (R^2) was evaluated to determine the proportion of variance in endogenous constructs explained by structural antecedents. The model accounted for 67.8% of the variance in Innovative Work Behavior ($R^2 = 0.678, R^2_{adj} = 0.672$), reflecting the strong explanatory power driven jointly by Smart Farming Solutions and Digital Competence. For the primary target construct, Farmer Performance, the model explained \$83.1\%\$ of total variance ($R^2 = 0.831, R^2_{adj} = 0.827$). This substantial variance explained in farm performance is driven by the proximal behavioral influence of Innovative Work Behavior rather than collinearity artifacts, as corroborated by low structural VIF statistics. Effect size assessments (f^2) further confirmed that Innovative Work Behavior exerts a strong effect on Farmer Performance ($f^2 = 1.845$). In contrast, direct effect sizes from Smart Farming Solutions ($f^2 = 0.008$) and Digital Competence ($f^2 = 0.000$) on Farmer Performance was nearly zero, indicating that direct structural paths contribute minimally to variance in performance without behavioral execution.

Direct structural pathways were evaluated using a nonparametric bootstrapping procedure with 5,000 resamples to test H_1 through H_5. Table 5 presents the path coefficients, standard errors, t-statistics, p-values, effect sizes, collinearity statistics, and empirical decisions for each direct relationship.

Table 5. Structural model assessment and direct hypotheses testing

Hypothesis	Structural Path	Path Coefficient (β)	Standard Error (SE)	t-statistic	p-value	Effect Size (f2)	VIF	Decision
H_1	Smart Farming Solutions → Farmer Performance	0.064	0.062	1.03	0.303	0.008	1.742	Not Supported
H_2	Digital Competence → Farmer Performance	-0.005	0.054	0.093	0.926	0	2.115	Not Supported
H_3	Smart Farming Solutions → Innovative Work Behavior	0.372	0.063	5.89	< 0.001	0.231	1.598	Supported
H_4	Digital Competence → Innovative Work Behavior	0.578	0.066	8.714	< 0.001	0.558	1.598	Supported
H_5	Innovative Work Behavior → Farmer Performance	0.872	0.061	14.361	< 0.001	1.845	2.318	Supported

The direct hypothesis testing results presented in Table 5 highlight the key relationships within the structural model. Hypothesis H_1, which proposed a direct positive relationship between Smart Farming Solutions and Farmer Performance, was not supported $(\beta = 0.064, t = 1.030, p = 0.303)$. Similarly, Hypothesis H_2, which examined the direct path from Digital Competence to Farmer Performance, was rejected $(\beta = -0.005, t = 0.093, p = 0.926)$. These results demonstrate that neither smart farming technologies nor digital competencies exert direct structural impacts on overall farmers' performance.

Conversely, Smart Farming Solutions demonstrated a positive and statistically significant direct relationship with Innovative Work Behavior $(\beta = 0.372, t = 5.890, p < 0.001)$, supporting Hypothesis H_3. Digital Competence also exhibited a strong positive influence on Innovative Work Behavior $(\beta = 0.578, t = 8.714, p < 0.001)$, confirming Hypothesis H_4. Finally, Hypothesis H_5 was strongly supported, as Innovative Work Behavior displayed a dominant direct positive effect on Farmer Performance $(\beta = 0.872, t = 14.361, p < 0.001)$. These findings suggest that technological tools and digital competencies serve primarily as foundational enablers that activate innovative behavior, which in turn drives ultimate agricultural performance.

4.5 Mediation Analysis

To evaluate the mediating role of Innovative Work Behavior between the exogenous antecedents and Farmer Performance, a structural mediation analysis was executed using a nonparametric bootstrapping procedure with 5,000 resamples. Following established PLS-SEM methodological standards, mediation mechanics are classified based on the joint statistical significance of both indirect and direct structural pathways. Specifically, indirect-only mediation (traditionally conceptualized as full mediation) is established when the indirect path achieves statistical significance, whereas the direct relationship remains non-significant. Statistical significance was evaluated using bias-corrected bootstrapped 95% confidence intervals (lower 2.5%, upper 97.5%), where intervals excluding zero confirmed a statistically significant indirect effect (Subhaktiyasa, 2024). Table 6 presents the mediation parameters and bootstrap results for H_6 and H_7.

Table 6. Mediation analysis and indirect effects

Hypothesis	Indirect Path	Indirect Effect (β)	SE	t-statistic	p-value	95% Bootstrapped CI [Lower, Upper]	Direct Effect (βdirect)	Total Effect (βtotal)	Mediation Type	Decision
H_6	SF → IWB → FP	0.325	0.062	5.264	< 0.001	[0.211, 0.453]	0.064 ($p = 0.303$)	0.389	Indirect-only	Supported
H_7	DC → IWB → FP	0.504	0.064	7.821	< 0.001	[0.381, 0.632]	-0.005 ($p = 0.926$)	0.499	Indirect-only	Supported

As presented in Table 6, Hypothesis H_6 proposed that Innovative Work Behavior mediates the relationship between Smart Farming Solutions and Farmer Performance. The empirical findings indicate a statistically significant positive indirect effect ($\beta = 0.325, t = 5.264, p < 0.001$), supported by a 95% bootstrapped confidence interval ranging from 0.211 to 0.453 (Subhaktiyasa, 2024). Given that the direct structural path from Smart Farming Solutions to Farmer Performance was non-significant ($\beta = 0.064, p = 0.303$), Hypothesis H_6 is confirmed as an indirect-only mediation. This demonstrates that Smart Farming Solutions impact agricultural performance exclusively when channeled through the behavioral engine of innovative work practices.

Similarly, Hypothesis H_7 examined the mediating role of Innovative Work Behavior in the relationship between Digital Competence and Farmer Performance. The bootstrap procedure yielded a robust indirect effect ($\beta = 0.504, t = 7.821, p < 0.001$), with a 95% bootstrapped confidence interval of $[0.381, 0.632]$ that strictly excludes zero (Subhaktiyasa, 2024). Because the direct path between Digital Competence and Farmer Performance was non-significant ($\beta = -0.005, p = 0.926$), Hypothesis H_7 is supported as an indirect-only mediation. Consequently, farmers' digital capabilities influence farm-level performance outcomes through the indispensable mediating conduit of innovative work behavior.

4.6 Discussion

4.6.1 The Direct Effects of Smart Farming Solutions and Digital Competence on Farmer Performance (H_1 & H_2)

The empirical findings reveal that neither Smart Farming Solutions ($\beta = 0.064, t = 1.030, p = 0.303$) nor Digital Competence ($\beta = -0.005, t = 0.093, p = 0.926$) exerts a statistically significant direct influence on Farmer Performance, leading to the rejection of H_1 and H_2. These unexpected results challenge the simplistic assumption that technological implementation or technical skill acquisition automatically yields direct improvements in agricultural output, farm revenue, or productivity. In smallholder rice farming contexts, the presence of modern technology or personal digital literacy does not independently alter yield per hectare or financial performance without active structural transformations in daily operational routines (Aranguri et al., 2026; Pacciani et al., 2026).

Smart farming devices, such as IoT sensors and automated irrigation systems, function as supportive tools rather than autonomous production engines (Abbasi et al., 2022; Dhanaraju et al., 2022). If smart farming tools are utilized passively without adaptive agronomic practices, their direct contribution to economic returns remains negligible (Taramuel-Taramuel et al., 2023; Wu et al., 2025). Similarly, digital competence reflects a farmer's capability to access information and navigate digital interfaces, but possessing digital knowledge does not generate revenue unless applied to operational decision-making(Aranguri et al., 2026; Sutami et al., 2025). This aligns with the findings of Zaman et al. (2023), who observed that technology adoption in rice farming fails to deliver financial benefits when disconnected from context-specific problem-solving. Consequently, physical equipment and individual skill sets represent latent resources that require behavioral conversion before a tangible economic value can be realized.

4.6.2 The Role of Smart Farming Solutions and Digital Competence in Fostering Innovative Work Behavior (H_3 & H_4)

In contrast to their direct paths, Smart Farming Solutions ($\beta = 0.372, t = 5.890, p < 0.001$) and Digital Competence ($\beta = 0.578, t = 8.714, p < 0.001$) demonstrate strong, positive direct associations with Innovative Work Behavior, fully supporting H_3 and H_4. These findings substantiate the integration of the Technology Acceptance Model Venkatesh and Davis (2000) and the Resource-Based View Barney (1991); (Kero & Bogale, 2023) within smallholder agricultural environments. Smart Farming Solutions provide the technological infrastructure and informational clarity that encourage farmers to generate, promote, and realize novel agricultural practices (AlEssa & Durugbo, 2022; Daniel et al., 2025). When farmers perceive digital agricultural tools as useful and manageable, their willingness to experiment with precision fertilization, targeted pest management, and optimized planting schedules increases significantly(Akkem et al., 2023; Duguma & Bai, 2024). Furthermore, Digital Competence functions as an essential internal resource under the Resource-Based View (Barney, 1991). High levels of digital literacy enable farmers to gather market intelligence, evaluate technical data, and communicate across digital platforms, thereby reducing the perceived risk of innovation (Brescianini & Luppi, 2026; Morales & Pacheco, 2024). Consequently, digital skills provide the cognitive foundation that transforms raw data into actionable and creative farm management solutions (Sutami et al., 2025).

4.6.3 Innovative Work Behavior as the Primary Driver of Farmer Performance (H_5)

Hypothesis H_5 posited that Innovative Work is positively related to Farmer Performance. The structural analysis confirms a strong direct path ($\beta = 0.872, t = 14.361, p < 0.001, f^2 = 1.845$), establishing Innovative Work Behavior as the central driver of agricultural success in the structural model. This finding emphasizes that proactive problem-solving, creative adaptation, and the actual execution of new ideas directly influence farm productivity, revenue, and overall income (AlEssa & Durugbo, 2022; Khan, Qureshi, Khan, & Aisha, 2026). In agricultural management, performance gains are achieved through behavioral execution, such as modifying crop distribution based on real-time weather data, negotiating direct sales via digital channels or refining resource allocation (Kasimati et al., 2024; Saptaria et al., 2026). Innovative work practices enable smallholder farmers to overcome environmental uncertainties, mitigate supply chain inefficiencies and optimize input costs (Batra et al., 2025; Ragazou et al., 2022). As corroborated by Morales and Pacheco (2024), individual innovation converts environmental opportunities into sustained performance outcomes. Therefore, active behavioral innovation is the primary operational mechanism through which agricultural productivity and profitability are sustained.

4.6.4 The Crucial Mediating Mechanism of Innovative Work Behavior (H_6 & H_7)

The mediation analysis confirms that Innovative Work Behavior serves as an indirect-only mediator between Smart Farming Solutions and Farmer Performance ($H6: \beta = 0.325, p < 0.001$), as well as between Digital Competence and Farmer Performance ($H7: \beta = 0.504, p < 0.001$). Because the direct paths (H_1 and H_2) were non-significant while the indirect paths were robust, the structural model demonstrated full indirect-only mediation mechanisms. These findings are effectively interpreted through the Ability-Motivation-Opportunity (AMO) theoretical framework (Bos-Nehles et al., 2023; Marin-Garcia & Martínez-Tomás, 2016). Smart Farming Solutions represent the opportunity (O) factor by offering advanced technological tools and diagnostic capabilities (Abiri et al., 2023; Sharma et al., 2022). Digital Competence embodies the ability (A) factor, providing the knowledge, skills, and literacy required to interpret digital resources (Brescianini & Luppi, 2026; Permatasari & Khair, 2026). However, neither Opportunity nor Ability directly alters performance outcomes without the operationalization of behavioral Motivation (M), represented here by Innovative Work Behavior (Bos-Nehles et al., 2023). Innovative Work Behavior acts as an operational bridge that translates technological potential and personal capability into tangible financial and physical outputs (Khan et al., 2026; Rurii & Nzengya Daniel, 2025). Without behavioral engagement, investments in smart farming technologies and digital skills remain unexploited.

4.6.5 Theoretical Contributions and Practical Implications
This study provides several theoretical and practical contributions to agricultural management and digital transformation. First, this study extends the Technology Acceptance Model Venkatesh and Davis (2000) by demonstrating that technology acceptance does not terminate at adoption or usage intensity. Instead, technology adoption serves as an upstream driver of proactive workplace behavior (Alka et al., 2026; Daniel et al., 2025). Second, it enriches the Resource-Based View Barney (1991); (Kero & Bogale, 2023) by showing that digital capabilities function as enabling resources requiring behavioral transformation to produce measurable performance outcomes. Third, by integrating TAM, RBV, and the AMO framework Bos-Nehles et al. (2023); Marin-Garcia and Martínez-Tomás (2016), this study offers an integrative model that explains how technological opportunities and individual capabilities interact to drive performance through behavioral innovation.

From a practical perspective, agricultural policymakers, extension agencies, and technology developers must shift their focus from mere hardware distribution to behavioral enablement Candraningrat et al. (2026); (Tahier, Nadirah, & Harahap, 2026). Training programs for smallholder rice farmers should go beyond basic digital literacy to emphasize practical problem solving, idea generation, and adaptive farm management (Permatasari & Khair, 2026; Sutami et al., 2025). Furthermore, digital platform developers should design intuitive interfaces that facilitate real-time experimentation and direct decision-making support (Qwaid et al., 2026; Shaikh et al., 2022). By cultivating an environment that encourages innovative work behaviors, agricultural stakeholders can maximize the economic returns of digital technology adoption in rural farming communities (Agustina et al., 2022; Suwarno & Aprianto, 2026).

5. Conclusions

5.1 Conclusion

This study concludes that Smart Farming Solutions and Digital Competence do not directly improve Farmer Performance, but both significantly enhance Innovative Work Behavior, which has a strong positive effect on Farmer Performance. The mediation analysis confirmed that Innovative Work Behavior fully mediated the relationship between Smart Farming Solutions, Digital Competence, and Farmer Performance. These findings indicate that the success of digital transformation in agriculture depends not only on technology adoption and digital competencies but also on farmers' ability to apply them through innovative work practices.

5.2 Research Limitations

This study is limited by its focus on 115 rice farmers in a single village, which may reduce the generalizability of its findings. In addition, the cross-sectional design does not capture changes in farmers' behavior and performance over time, and the study only examines four variables.

5.3 Suggestions and Directions for Future Research

Future studies should involve larger and more diverse samples from different agricultural regions and commodities. Researchers are also recommended to adopt longitudinal designs and include additional variables, such as government support, agricultural extension services, technological readiness, and organizational support, to provide a more comprehensive understanding of digital transformation and farmer performance.

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Author Contributions

MPP contributed to the conceptualization, formal analysis, and preparation of the original manuscript. HH contributed to the methodology, validation, resources, data curation, manuscript review, and editing. YA contributed to software development, investigation, and visualization. All authors have read and approved the final version of the manuscript.

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