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The effect of digital readiness and technology acceptance on smart farming adoption in agribusiness management

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ABSTRACT

This study examines the effect of digital readiness and technology acceptance on smart farming adoption intention and agribusiness management performance in Lampung Province, Indonesia. The agribusiness aspects examined in this study focus on operational efficiency, productivity, resource management, supply chain coordination, and market access. A quantitative explanatory design was applied using survey data from 150 respondents consisting of farmers, agribusiness actors, farmer group managers, agricultural extension agents, and agribusiness-related students or academics with relevant knowledge of digital agricultural technology. The research model includes Digital Readiness, Perceived Usefulness, and Perceived Ease of Use as antecedent variables, Smart Farming Adoption Intention as a mediating variable, and perceived Agribusiness Management Performance as the outcome variable. Data were analyzed using Partial Least Squares Structural Equation Modeling. The results show that digital readiness, perceived usefulness, and perceived ease of use significantly influence smart farming adoption intention. Adoption intention also significantly improves agribusiness management performance and mediates the relationship between digital readiness, technology acceptance, and performance. Perceived usefulness is the strongest driver of adoption intention, indicating that agribusiness actors are more willing to adopt smart farming when they perceive clear managerial benefits. This study contributes to technology acceptance literature by positioning smart farming adoption as a managerial transformation process, not only as a technological decision.

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1. INTRODUCTION

Smart farming adoption has become an important issue in agribusiness management as agriculture faces increasing pressure from climate change, food security risks, resource scarcity, and the demand for more efficient production systems (Klerkx et al., 2019). Digital agriculture, including smart farming technologies, is increasingly viewed as a strategic approach to improving productivity, sustainability, and data-based decision-making in agricultural enterprises (Fielke et al., 2020). In this study, smart farming is not treated merely as the use of agricultural technology, but as a managerial transformation that affects how agribusiness actors plan production, allocate resources, coordinate supply chains, improve market access, and manage operational risks (Wolfert et al., 2017).

Lampung Province was selected as the research location because agriculture remains one of the most important economic sectors in the region. The agricultural, forestry, and fisheries sector contributes substantially to Lampung's regional economy, while the province also faces challenges related to productivity improvement, digital infrastructure gaps, farmer regeneration, and market competitiveness (Eastwood et al., 2019). This condition makes Lampung a relevant context for examining whether digital readiness and technology acceptance can support smart farming adoption and improve agribusiness management performance (Giua et al., 2022). In addition, the respondent profile in this study shows that more than half of respondents knew about smart farming but had not yet used it, indicating that awareness already exists while actual implementation remains limited (Piancharoenwong & Badir, 2024).

Previous studies have shown that smart farming adoption is influenced by technological, behavioral, and managerial factors (Wang & Dong, 2023). Farmers' intention to adopt smart farming technologies is shaped by performance expectations, social influence, perceived complexity, trust, facility conditions, and perceived benefits (X. Yu et al., 2024). Studies on agricultural digital services also show that adoption intention and facility conditions influence technology use behavior (Dong et al., 2022). These findings suggest that smart farming adoption should be analyzed through an integrated framework involving digital readiness and technology acceptance (Arthur et al., 2024).

However, three gaps remain in the literature. First, many studies focus on adoption intention, but fewer connect adoption intention with broader agribusiness management outcomes such as operational efficiency, productivity, resource management, supply chain coordination, and market access (Peña-Holguín et al., 2025). Second, previous studies often treat digital readiness as a supporting condition, but do not sufficiently examine its direct and indirect roles in improving management performance (Kamilaris & Prenafeta-Boldú, 2018). Third, the distinction between research gap and novelty is often unclear in smart farming adoption studies (Bacco et al., 2019). The research gap in this study refers to the limited empirical explanation of how digital readiness and technology acceptance jointly influence adoption intention and perceived agribusiness management performance. The novelty lies in integrating Digital Readiness, Perceived Usefulness, Perceived Ease of Use, Smart Farming Adoption Intention, and Agribusiness Management Performance into one structural model in the context of Lampung agribusiness.

This study aims to examine the effect of digital readiness and technology acceptance on smart farming adoption intention and agribusiness management performance. Specifically, this study investigates whether Digital Readiness, Perceived Usefulness, and Perceived Ease of Use influence Smart Farming Adoption Intention and Agribusiness Management Performance, and whether Smart Farming Adoption Intention mediates these relationships. The findings are expected to provide theoretical contributions to technology acceptance and digital agribusiness literature, as well as practical recommendations for strengthening digital literacy, infrastructure readiness, technical assistance, and evidence-based smart farming promotion in developing agricultural regions (Dhanaraju et al., 2022).

2. RESEARCH METHOD

Research Design and Study Area

This study employed a quantitative explanatory research design to examine the effect of digital readiness and technology acceptance on smart farming adoption intention and agribusiness management performance (Mishra et al., 2024). This design was selected because the study aimed to test causal relationships among latent variables using a structural model (Lisa et al., 2025). The research was conducted in Lampung Province, Indonesia. Lampung was selected because agriculture is one of the major sectors supporting the regional economy, while digital transformation in agribusiness still requires stronger infrastructure readiness, digital literacy, and adoption support (A. Cao et al., 2025).

The research model consists of Digital Readiness, Perceived Usefulness, and Perceived Ease of Use as antecedent variables, Smart Farming Adoption Intention as a mediating variable, and Agribusiness (Larasati et al., 2024) Management Performance as the outcome variable. In this study, smart farming adoption was positioned as an intention-based construct, not as confirmed

long-term actual adoption (Agussabti et al., 2022). Therefore, the results explain respondents' willingness and readiness to adopt smart farming technology rather than actual post-adoption behavior (Chen et al., 2024).

Population, Sample, and Respondent Criteria

The population of this study consisted of individuals involved in or familiar with agribusiness activities and digital agricultural technology in Lampung Province. Respondents included farmers, agribusiness actors, farmer group managers, agricultural extension agents, and students or academics in agribusiness-related fields. Students and academics were included only when they had direct academic or practical exposure to agribusiness or smart farming, because they were considered capable of providing informed assessments of digital readiness and technology adoption intention. However, they were not categorized as actual farm owners unless they were also directly involved in agribusiness activities (Poorna et al., 2025).

A purposive sampling technique was applied to ensure that the respondents met the research objectives. The inclusion criteria were: respondents had knowledge of agribusiness activities, had direct or indirect exposure to digital agricultural technology, were located in or related to agribusiness activities in Lampung Province, and were willing to complete the questionnaire. The exclusion criteria were: respondents who had no knowledge of agribusiness, respondents who were not familiar with digital agricultural technology, and respondents who provided incomplete answers. A total of 150 valid responses were collected and analyzed. This sample size was considered adequate for PLS-SEM because it exceeded the minimum requirement based on the ten-times rule, particularly for a model with three main predictors of the mediating construct (Hermiliana et al., 2025).

Variables and Measurement

This study used five latent variables: Digital Readiness, Perceived Usefulness, Perceived Ease of Use, Smart Farming Adoption Intention, and Agribusiness Management Performance. Digital Readiness refers to the extent to which agribusiness actors have access, facilities, skills, and support to use digital technology in agribusiness activities (Pranadita & Purwanti, 2026). Perceived Usefulness refers to the belief that smart farming can improve productivity, efficiency, decision-making, and risk prediction. Perceived Ease of Use refers to the belief that smart farming technology is easy to learn, understand, and operate. Smart Farming Adoption Intention refers to the willingness of agribusiness actors to use, continue using, recommend, and allocate resources for smart farming. Agribusiness Management Performance refers to perceived improvement in operational efficiency, productivity, resource management, supply chain coordination, and market access (Rahmawati et al., 2025). The research instrument consisted of 20 statement items, with each construct measured using four indicators. All items were adapted from the Technology Acceptance Model, digital readiness perspective, and agribusiness management literature, then adjusted to the context of smart farming and agribusiness activities. Each item was measured using a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. The operational definitions and indicators of the variables are presented in Table 1.

Table 1. Operational definition of research variables

Variable	Code	Operational Definition	Indicators
Digital Readiness	X1	The extent to which agribusiness actors have access, facilities, skills, and support to use digital technology in agribusiness activities.	Internet access, digital devices, digital skills, technical support
Perceived Usefulness	X2	The extent to which agribusiness actors believe that smart farming can improve productivity, efficiency, and decision-making.	Productivity improvement, cost efficiency, data-based decision-making, risk prediction
Perceived Ease of Use	X3	The extent to which agribusiness actors perceive smart farming technology as easy to learn and use.	Ease of learning, ease of use, clear instructions, low complexity
Smart Farming Adoption Intention	M	The willingness of agribusiness actors to use, continue using, recommend, and allocate resources for smart farming.	Intention to use, continuance intention, recommendation intention, investment readiness
Agribusiness Management Performance	Y	The extent to which digital technology and smart farming improve agribusiness management outcomes.	Operational efficiency, business productivity, resource management, supply chain and marketing improvement

Data Collection Procedure

Data were collected using a structured questionnaire distributed to respondents who met the inclusion criteria. The questionnaire was designed to capture respondents' perceptions of digital readiness, technology acceptance, smart farming adoption intention, and agribusiness management performance. Before analysis, the collected responses were screened to ensure completeness and relevance to the research criteria (Chuang et al., 2020). Incomplete responses and responses from individuals who did not meet the respondent criteria were excluded from the analysis. Because this study used cross-sectional survey data, all variables were measured at one point in time. Therefore, the interpretation of causality is based on theoretical justification and structural modeling, not on longitudinal observation (Bagheri et al., 2024). In addition, Agribusiness Management Performance was measured using perceived performance indicators rather than audited financial records, production records, or long-term operational data. This limitation was considered in interpreting the findings.

Data Analysis Technique

Data were analyzed using Partial Least Squares Structural Equation Modeling with SmartPLS. PLS-SEM was selected because it is suitable for analyzing complex structural models involving multiple latent variables, mediation effects, and prediction-oriented relationships (Yaakub et al., 2025). The analysis was conducted in two stages: measurement model evaluation and structural model evaluation. The measurement model was evaluated using outer loading, Cronbach's Alpha, Composite Reliability, Average Variance Extracted, and discriminant validity. Indicator reliability was accepted when outer loading values were above 0.70. Internal consistency reliability was assessed using Cronbach's Alpha and Composite Reliability, with values above 0.70 considered acceptable. Convergent validity was evaluated using Average Variance Extracted, with values above 0.50 considered valid. Discriminant validity was assessed using the Heterotrait-Monotrait Ratio, with values below 0.90 indicating adequate discriminant validity.

The structural model was evaluated using R-square, path coefficients, t-statistics, p-values, and specific indirect effects. Hypotheses were considered supported when the t-statistic was greater than 1.96 and the p-value was below 0.05. The mediation effect of Smart Farming Adoption Intention was examined through specific indirect effects to determine whether adoption intention mediated the relationships between Digital Readiness, Perceived Usefulness, Perceived Ease of Use, and Agribusiness Management Performance.

3. RESULTS AND DISCUSSIONS

Respondent Profile

This study involved 150 respondents from Lampung Province who were related to agribusiness activities and had knowledge of digital agricultural technology. The respondent profile was analyzed to describe gender, age, education level, role in agribusiness, length of involvement, commodity type, and smart farming knowledge. The respondent characteristics are presented in Table 2.

Table 2. Respondent profile

Profile	Category	Frequency	Percentage
Gender	Female	78	52.0%
	Male	72	48.0%
Age	20–30 years	67	44.7%
	31–40 years	43	28.7%
	41–50 years	20	13.3%
	> 50 years	12	8.0%
	< 20 years	8	5.3%
Education Level	Bachelor	72	48.0%
	Senior High School/Vocational School	42	28.0%
	Diploma	20	13.3%
	Postgraduate	16	10.7%
Role in Agribusiness	Farmer	47	31.3%
	Agribusiness actor	32	21.3%
	Agribusiness student/academic	25	16.7%
	Agricultural extension agent	25	16.7%
	Farmer group manager	21	14.0%

Profile	Category	Frequency	Percentage
Length of Involvement	1–3 years	38	25.3%
	4–6 years	31	20.7%
	> 10 years	30	20.0%
	7–10 years	26	17.3%
	< 1 year	25	16.7%
Commodity Type	Food crops	50	33.3%
	Livestock	32	21.3%
	Horticulture	28	18.7%
	Plantation	26	17.3%
	Fisheries	14	9.3%
Smart Farming Knowledge	Know but have not used	77	51.3%
	Have used	37	24.7%
	Do not yet have in-depth knowledge	36	24.0%

Table 3 shows that the respondents were relatively balanced by gender, with 52.0% female and 48.0% male respondents. Most respondents were in the 20–30-year age group, followed by the 31–40-year group, indicating that the sample was dominated by productive-age respondents who are generally more familiar with digital technology. In terms of education, most respondents had a bachelor's degree, followed by senior high school or vocational school graduates. Professionally, farmers represented the largest group, followed by agribusiness actors, agricultural extension agents, agribusiness students or academics, and farmer group managers. Food crops were the dominant commodity type. An important finding from the respondent profile is that 51.3% of respondents knew about smart farming but had not yet used it, while only 24.7% had used smart farming. This condition confirms that smart farming awareness already exists in Lampung agribusiness, but actual implementation remains limited. Therefore, the sample is relevant for examining digital readiness, technology acceptance, and smart farming adoption intention.

Measurement Model Evaluation

The measurement model was evaluated to ensure that all indicators were valid and reliable in measuring their respective constructs. Indicator reliability was assessed through outer loading values, internal consistency was evaluated using Cronbach's Alpha and Composite Reliability, convergent validity was assessed using Average Variance Extracted, and discriminant validity was examined using the Heterotrait-Monotrait Ratio.

Table 3. Outer loading results

Construct	Indicator	Outer Loading	Interpretation
Digital Readiness	X1.1	0.812	Valid
Digital Readiness	X1.2	0.784	Valid
Digital Readiness	X1.3	0.806	Valid
Digital Readiness	X1.4	0.741	Valid
Perceived Usefulness	X2.1	0.846	Valid
Perceived Usefulness	X2.2	0.801	Valid
Perceived Usefulness	X2.3	0.773	Valid
Perceived Usefulness	X2.4	0.759	Valid
Perceived Ease of Use	X3.1	0.827	Valid
Perceived Ease of Use	X3.2	0.792	Valid
Perceived Ease of Use	X3.3	0.768	Valid
Perceived Ease of Use	X3.4	0.734	Valid
Smart Farming Adoption Intention	M1.1	0.838	Valid
Smart Farming Adoption Intention	M1.2	0.821	Valid
Smart Farming Adoption Intention	M1.3	0.779	Valid
Smart Farming Adoption Intention	M1.4	0.746	Valid
Agribusiness Management Performance	Y1.1	0.861	Valid
Agribusiness Management Performance	Y1.2	0.843	Valid
Agribusiness Management Performance	Y1.3	0.817	Valid
Agribusiness Management Performance	Y1.4	0.782	Valid

Source: Processed research data

As shown in Table 3, all indicators have outer loading values above 0.70, ranging from 0.734 to 0.861. These results indicate that all indicators have adequate reliability in representing their latent constructs. Therefore, no indicator was removed from the model. The highest loading

value is found in Y1.1, which represents operational efficiency in Agribusiness Management Performance. This indicates that operational efficiency is the most representative indicator of perceived management performance in the context of smart farming adoption. Meanwhile, the lowest loading value is found in X3.4, which reflects the perception that smart farming is not too complicated. Although this value is still acceptable, it suggests that perceptions of technological simplicity may vary among respondents.

Table 4. Construct reliability and validity

Construct	Cronbach's Alpha	Composite Reliability	AVE	Interpretation
Digital Readiness	0.853	0.866	0.618	Reliable and valid
Perceived Usefulness	0.742	0.873	0.633	Reliable and valid
Perceived Ease of Use	0.812	0.862	0.610	Reliable and valid
Smart Farming Adoption Intention	0.814	0.874	0.635	Reliable and valid
Agribusiness Management Performance	0.830	0.896	0.683	Reliable and valid

Source: Processed research data

Table 4 shows that all constructs have Cronbach's Alpha and Composite Reliability values above 0.70, indicating adequate internal consistency reliability. In addition, all Average Variance Extracted values are above 0.50, confirming convergent validity. These results show that Digital Readiness, Perceived Usefulness, Perceived Ease of Use, Smart Farming Adoption Intention, and Agribusiness Management Performance are reliable and valid constructs. The highest AVE value is found in Agribusiness Management Performance, indicating that its indicators strongly explain the construct, particularly in relation to operational efficiency, productivity, resource management, supply chain coordination, and marketing improvement.

Table 5. Discriminant validity using HTMT

Construct	X1	X2	X3	M	Y
Digital Readiness	—				
Perceived Usefulness	0.476	—			
Perceived Ease of Use	0.547	0.440	—		
Smart Farming Adoption Intention	0.627	0.542	0.523	—	
Agribusiness Management Performance	0.701	0.565	0.509	0.702	—

The HTMT results in Table 5 show that all values are below the recommended threshold of 0.90. This confirms that each construct is empirically distinct from the others. The highest HTMT value is found between Smart Farming Adoption Intention and Agribusiness Management Performance. This relationship is theoretically reasonable because adoption intention is expected to be closely associated with perceived performance improvement. However, the value remains below the threshold, indicating that the two constructs are not statistically redundant. Overall, the measurement model meets the requirements of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

Structural Model Evaluation and Hypothesis Testing

The structural model was evaluated to examine the explanatory power of the model and the strength of the relationships among variables. The evaluation was conducted using R-square values, path coefficients, t-statistics, and p-values. The R-square results are presented in Table 6.

Table 6. R-square results

Endogenous Construct	R-Square	Interpretation
Smart Farming Adoption Intention	0.704	Strong
Agribusiness Management Performance	0.681	Moderate to strong

The R-square value of Smart Farming Adoption Intention is 0.704, meaning that Digital Readiness, Perceived Usefulness, and Perceived Ease of Use explain 70.4% of the variance in adoption intention. This indicates that smart farming adoption intention among agribusiness actors is shaped by the combined influence of digital capability, perceived benefits, and perceived ease of use. The R-square value of Agribusiness Management Performance is 0.681, indicating that 68.1% of the variance in perceived management performance is explained by Digital Readiness,

Perceived Usefulness, Perceived Ease of Use, and Smart Farming Adoption Intention. These values show that the model has adequate explanatory power for understanding smart farming adoption and agribusiness management performance. The structural model results are visualized in Figure 1. The figure presents the outer loading values of the indicators, the path coefficients among latent variables, and the R-square values of the endogenous constructs. This visualization provides an overview of both the measurement and structural relationships before the detailed hypothesis testing results are presented.

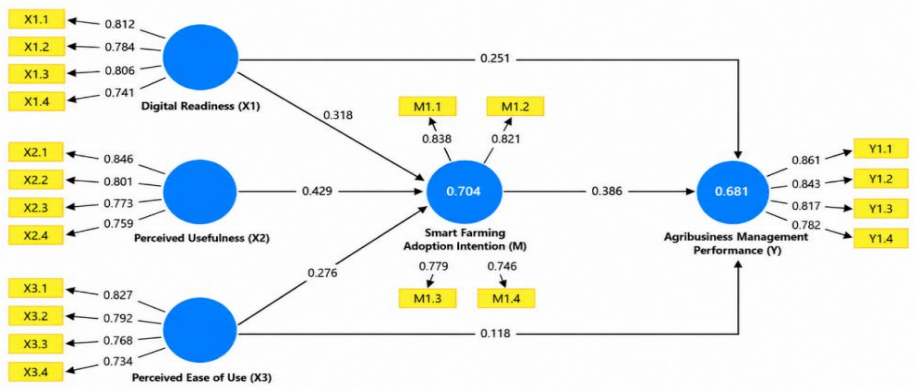

Figure 1. PLS-SEM structural model results

Table 7. Hypothesis testing results

Hypothesis	Path	Path Coefficient	T-Statistic	P-Value	Result
H1	Digital Readiness → Smart Farming Adoption Intention	0.318	4.216	0.000	Supported
H2	Perceived Usefulness → Smart Farming Adoption Intention	0.429	6.538	0.000	Supported
H3	Perceived Ease of Use → Smart Farming Adoption Intention	0.276	3.947	0.000	Supported
H4	Smart Farming Adoption Intention → Agribusiness Management Performance	0.386	5.724	0.000	Supported
H5	Digital Readiness → Agribusiness Management Performance	0.251	3.268	0.001	Supported
H6	Perceived Usefulness → Agribusiness Management Performance	0.307	4.491	0.000	Supported
H7	Perceived Ease of Use → Agribusiness Management Performance	0.118	2.014	0.044	Supported

Table 7 shows that all direct hypotheses are supported. Digital Readiness has a positive and significant effect on Smart Farming Adoption Intention, indicating that internet access, digital devices, digital skills, and technical support are important enabling factors for smart farming adoption. Digital Readiness also has a significant effect on Agribusiness Management Performance, showing that readiness to use digital technology can contribute to better agribusiness management practices. Perceived Usefulness has the strongest effect on Smart Farming Adoption Intention. This finding indicates that agribusiness actors are more willing to adopt smart farming when they perceive clear managerial benefits, such as productivity improvement, cost efficiency, data-based decision-making, and risk prediction. This result is consistent with the Technology Acceptance Model, which emphasizes perceived usefulness as a major determinant of technology adoption. In the agribusiness context, usefulness becomes particularly important because actors tend to evaluate technology based on its practical contribution to production, resource allocation, market access, and risk management (Dai & Cheng, 2022).

Perceived Ease of Use also has a positive and significant effect on Smart Farming Adoption Intention, although its coefficient is lower than Perceived Usefulness and Digital Readiness. This suggests that ease of use supports adoption intention, but it is not the dominant factor. Agribusiness actors may tolerate a certain level of technological complexity when smart

farming provides clear business and managerial benefits. Therefore, ease of use should be understood as a supporting factor, while perceived usefulness acts as the main driver of adoption intention.

Smart Farming Adoption Intention has a positive and significant effect on Agribusiness Management Performance. This finding confirms that performance improvement does not depend only on infrastructure or positive perceptions of technology, but also on the willingness of users to adopt, continue using, recommend, and allocate resources for smart farming (K. Cao et al., 2026). The direct effects of Digital Readiness, Perceived Usefulness, and Perceived Ease of Use on Agribusiness Management Performance are also significant. Among these variables, Perceived Usefulness has the strongest direct effect on performance, indicating that agribusiness management performance is more likely to improve when smart farming is perceived as useful for managerial decision-making and operational improvement (Pradana & Salamat, 2025).

Mediation Effect

The mediation effect was examined to determine whether Smart Farming Adoption Intention mediates the relationship between Digital Readiness, Perceived Usefulness, Perceived Ease of Use, and Agribusiness Management Performance. The results are presented in Table 8.

Table 8. Specific indirect effect results

Hypothesis	Indirect Path	Indirect Effect	T-Statistic	P-Value	Result
H8	Digital Readiness → Smart Farming Adoption Intention → Agribusiness Management Performance	0.123	3.421	0.001	Supported
H9	Perceived Usefulness → Smart Farming Adoption Intention → Agribusiness Management Performance	0.166	4.716	0.000	Supported
H10	Perceived Ease of Use → Smart Farming Adoption Intention → Agribusiness Management Performance	0.107	3.158	0.002	Supported

The mediation results show that Smart Farming Adoption Intention significantly mediates all relationships between the antecedent variables and Agribusiness Management Performance. The strongest indirect effect is found in the relationship between Perceived Usefulness and Agribusiness Management Performance through Smart Farming Adoption Intention. This means that perceived managerial benefits become more influential when they are transformed into a concrete intention to adopt smart farming (J. Yu et al., 2025). In other words, agribusiness actors who perceive smart farming as useful are more likely to develop adoption intention, and this intention subsequently contributes to perceived improvement in management performance.

The indirect effect of Digital Readiness on Agribusiness Management Performance through Smart Farming Adoption Intention is also significant. This indicates that digital infrastructure, digital devices, digital skills, and technical support contribute to performance not only directly, but also indirectly by strengthening adoption intention. Therefore, digital readiness programs should not only focus on providing access and facilities, but also on increasing users' willingness to apply smart farming in agribusiness activities (Kemp et al., 2024).

The indirect effect of Perceived Ease of Use is significant but has the smallest coefficient. This result suggests that ease of use supports management performance through adoption intention, but its influence is weaker than perceived usefulness and digital readiness (Bekee et al., 2024). This finding implies that smart farming development should not only simplify technology interfaces, but also demonstrate concrete benefits for productivity, efficiency, resource management, supply chain coordination, and market access.

Overall, the findings indicate that smart farming adoption in agribusiness management is shaped by the interaction between readiness, perceived usefulness, perceived ease of use, and adoption intention (Tamimi, 2024). Theoretically, this study extends technology acceptance literature by integrating digital readiness and perceived agribusiness management performance into one structural model (Zaineldeen et al., 2020). Practically, the findings suggest that smart farming programs in Lampung Province should prioritize digital infrastructure, digital literacy, technical assistance, demonstration-based learning, and evidence-based promotion of smart farming benefits. However, the findings should be generalized carefully because the sample

includes respondents with relatively high educational backgrounds and respondents who already had some knowledge of digital agricultural technology (Pienwisetkaew et al., 2025). Future studies should include broader farmer groups, compare regions, and examine actual long-term adoption behavior.

4. CONCLUSION

This study concludes that smart farming adoption in Lampung agribusiness is shaped by the interaction between digital readiness, technology acceptance, and adoption intention. The main contribution of this study is the development of an integrated model that connects Digital Readiness, Perceived Usefulness, Perceived Ease of Use, Smart Farming Adoption Intention, and perceived Agribusiness Management Performance. The agribusiness performance aspects emphasized in this study include operational efficiency, productivity, resource management, supply chain coordination, and market access.

The findings show that perceived usefulness is the most important factor in strengthening adoption intention. This indicates that smart farming programs should not only introduce technology, but also demonstrate clear managerial benefits for agribusiness actors. Digital readiness and ease of use also support adoption, but their impact becomes stronger when they encourage users' intention to adopt smart farming. The mediation results confirm that adoption intention functions as a behavioral bridge between readiness, acceptance, and perceived management performance.

Practically, this study suggests that smart farming development in Lampung should prioritize four strategies: improving rural digital infrastructure, strengthening digital literacy and technical assistance, providing demonstration-based evidence of smart farming benefits, and developing affordable financing or partnership schemes for agribusiness actors. This study is limited by its cross-sectional design, purposive sampling, and reliance on perceived performance rather than audited productivity or long-term adoption data. Future research should examine actual smart farming usage, compare different agricultural regions, include smallholder farmers with lower digital access, and apply longitudinal designs to evaluate real performance changes after adoption.

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