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Factors Influencing Rice Farmers' Intention of Smart Farming Technology in Kanigoro Village, Malang Regency

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ABSTRACT

The adoption of smart farming technology among rice farmers in Kanigoro Village, Pagelaran Subdistrict, remains low despite the availability of tools designed to enhance agricultural efficiency. Technologies such as the Smart Soil Sensor and Bird Control Sound System are still underutilized, reflecting a gap between technological availability and farmer adoption. This study analyzes the influence of attitude, subjective norm, and perceived behavioral control on farmers' intention to adopt smart farming technology, using the Theory of Planned Behavior (TPB) as the analytical framework. A total of 100 farmers were surveyed through structured questionnaires and direct interviews, with data analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that all three variables significantly affect intention: attitude ($\beta = 0.19$, $p = 0.023$), subjective norm ($\beta = 0.33$, $p < 0.001$), and perceived behavioral control ($\beta = 0.42$, $p < 0.001$). Perceived behavioral control emerged as the strongest predictor, followed by subjective norm and attitude. These findings highlight that enhancing adoption requires not only promoting positive attitudes but also strengthening social support and improving farmers' confidence in their ability to access and operate smart farming technologies.

***Keywords**:attitude, intention, perceived behavioral control, smart farming, subjective norm*

BACKGROUND

Birds represent one of the most difficult pests for rice farmers to control, as their attacks are frequent, unpredictable, and labor-intensive to mitigate. In severe cases, such infestations can devastate productivity, with reported yield losses reaching 50–80% (Ministry of Agriculture of Indonesia, 2023), thereby posing a serious threat to farmer livelihoods and local food security. According to Ridwan et al. (2023), bird attacks can reduce rice productivity by up to 20–30%, directly threatening farmer income and local food security. Smart farming technologies, such as the Bird Control Sound System, have been introduced as innovative solutions to address this problem, alongside other tools like Smart Soil Sensors that improve input efficiency and crop monitoring. Smart farming, in principle, offers a strategic pathway to enhance farmer welfare and strengthen local food security (Rachmawati, 2021). However, despite its potential, the implementation of such technologies continues to face barriers due to the low levels of intention and adoption among farmers. This adoption gap raises fundamental questions about the factors influencing farmers' willingness to embrace smart farming innovations.

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To understand these underlying factors, this study employs the Theory of Planned Behavior (TPB) as its analytical framework. Originally proposed by (Ajzen, 2020), TPB posits that behavioral intention is shaped by three key constructs: attitude toward the behavior, subjective norm, and perceived behavioral control. This framework has been widely validated in explaining adoption behavior in agriculture and digital innovation (Waiswa et al., 2024; Wilheppi et al., 2023; Zamil et al., 2024), yet remains underexplored in the context of Indonesian rice farmers. Based on this theoretical foundation, the hypothesis proposed is that rice paddy farmers' intention to adopt smart farming technology is significantly influenced by their attitude toward the technology, subjective norm from their social environment, and perceived behavioral control over its use.

Smart farming is expected to serve as a strategic solution for improving farmer welfare and strengthening local food security (Rachmawati, 2021). However, in reality, there is an implementation gap in this technology, as it still faces obstacles due to farmers' low intention and limited adoption. This low level of adoption raises a fundamental question regarding the key factors that influence farmers' intention to utilize smart farming innovations. This research is important because identifying the determinants of intention is the first step in designing effective interventions—such as targeted training, financial subsidies, and technical support—that can accelerate adoption (Kusumawati et al., 2024; Sawaluddin & Lidayanti, 2024). The object of this study, therefore, is to analyze the factors influencing the intention of rice farmers in Kanigoro Village, Pagelaran District, Malang Regency, to adopt smart farming technology, a region where innovations have been introduced but adoption remains limited.

RESEARCH METHODS

This study employs a quantitative method to analyze the influence of attitude, subjective norm, and perceived behavioral control on farmers' intention to use smart farming technology. This design was chosen because the research aims to objectively explain the relationships between variables based on numerical data collected from the field. The subjects of this research are rice farmers in Kanigoro Village, Pagelaran District, Malang Regency, a region that has received assistance for Internet of Things (IoT)-based agricultural technologies, such as the Smart Soil Sensor and Bird Control Sound System. The primary instrument for this study is a structured questionnaire using a 1–5 Likert scale, designed to measure the four laten variables: attitude, subjective norm, perceived behavioral control, and adoption intention.

Table 1. Laten Variable and Manifes Variable

Source	Laten Variable	Manifes Variable
Retnaningtyas et al. (2024)	Attitude	I believe that smart farming will increase my agricultural productivity I feel that smart farming will reduce production costs I think that adopting smart farming technology will benefit the environment
Waiswa et al. (2024)	Subjective Norm	My family supports the use of smart farming technology Other farmers I know recommend the use of smart farming

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Source	Laten Variable	Manifes Variable
		The government or local institutions encourage me to use smart farming
Zamil et al. (2024)	Perceived Behavioral Control	I have the resources necessary to adopt smart farming technology I am confident in my ability to operate smart farming technology
Nugraha et al. (2024)	Intention	I intend to try smart farming technology in the near future I plan to use smart farming technology as part of my farming practices

The research was conducted from October to December 2024 and used primary data. According to Ramdhan (2021), primary data were obtained through direct interviews using questionnaires. The sampling technique used was accidental sampling, with a total of 100 farmer respondents, a number determined by calculations using Lemeshow's formula. Accidental sampling was chosen due to field constraints, as not all farmers were available simultaneously, but only those actively cultivating rice in Kanigoro Village were included. To minimize bias, the sample size was calculated using Lemeshow's formula, and respondent characteristics (age, education, experience, group membership) were monitored to reflect the population profile. Moreover, since the study employed PLS-SEM, which emphasizes testing relationships between constructs rather than population estimates, the method remained appropriate for the theoretical model.

The operational definitions of the variables are based on the Theory of Planned Behavior (Ajzen, 2020). The attitude variable is measured by beliefs regarding the benefits of smart farming in terms of productivity, cost efficiency, and environmental impact (Retnaningtyas et al., 2024). The subjective norm is measured through perceived support from family, other farmers, and the government (Waiswa et al., 2024). Perceived behavioral control includes farmers' beliefs about the ease of use and the availability of resources (Zamil et al., 2024). Intention is measured by the desire and plans of farmers to use smart farming technology (Nugraha et al., 2024).

The data were analyzed using Descriptive Statistics and Partial Least Squares Structural Equation Modeling (PLS-SEM) with WarpPLS 7.0 software. PLS-SEM was employed to simultaneously test the relationships between the latent variables and their indicators, as well as to assess the strength of each variable's influence within the model:

$$Y = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \zeta$$

Where:
Y = Intention to adopt smart farming
X_1 = Attitude
X_2 = Subjective Norm
X_3 = Perceived Behavioral Control
$\beta_1 \beta_2 \beta_3$ = Path coefficients showing the influence of each exogenous variable
ζ = Error term

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RESULT AND DISCUSSION

This study will analyze the descriptive statistics of each research variable, examine how the factors of attitude, subjective norm, and perceived behavioral control influence farmers' intention to adopt smart farming technology, and assess the extent to which the adoption of this technology can be promoted through a behavioral approach based on the Theory of Planned Behavior (TPB).

Respondent Characteristics

The analysis of respondent characteristics includes age, gender, education, farming experience, income, and secondary employment. This analysis is crucial for understanding the farmer profile, as these factors can influence attitude, subjective norm, perceived behavioral control, and the intention to adopt smart farming technology. Understanding these characteristics helps in evaluating the readiness for and potential implementation of smart farming within the research area.

Table 1. Respondent Characteristic

Characteristic	Items	Percentage (%)
Age (Years)	31-40	7
	41-50	20
	51-60	41
	61-70	27
	71-80	3
	81-90	2
	Total	**100**
Gender	Man	94
	Woman	6
	Total	**100**
Last Education	Not in School	2
	Elementary	49
	Not Completed	6
	Junior High	20
	Senior High	18
	Bachelor/Diploma	5
	Total	**100**
Farming Period (Years)	1-10	14
	11-20	16
	21-30	32
	31-40	21
	41-50	11
	51-60	6
	Total	**100**
Side Job	Have	38
	Don’t Have	62
	Total	**100**
Farmer’s Group	Part of	55
	Not Part of	45
	Total	**100**

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Characteristic	Items	Percentage (%)
Extension	Have	57
	Never Have	43
	Total	**100**

Source: Primary Data, 2025

The respondents in this study were predominantly male (94%) and aged between 51–60 years (41%), reflecting the dominance of the productive age group. According to research by Effendy & Pratiwi (2020), the productive age range is between 47 and 62 years. The majority of respondents had an Elementary School education as their highest level of attainment (49%), with over 20 years of farming experience. A total of 62% of respondents had no secondary job's and relied on agriculture as their primary source of income, while the remaining 38% had additional jobs such as construction laborers, livestock farmers, or traders. Furthermore, 55% were members of farmer groups, and 57% had previously attended agricultural extension activities. These characteristics indicate that while the respondents possess considerable experience and high involvement in agricultural activities, they still face challenges regarding technological literacy and access to information, which affects their readiness to adopt smart farming technology.

Descriptive Statistics

Descriptive statistics for the variables of attitude, subjective norm, perceived behavioral control, and intention are used to illustrate the data trends within the Theory of Planned Behavior (TPB) framework. This analysis evaluates farmers' perspectives and motivations towards smart farming, assesses their level of acceptance and the potential for technology adoption, and identifies aspects that require greater attention for successful implementation.

Table 2. Descriptive Statistics of Variables

Variable Indicators		Min.	Max.	Mean	Category
Attitude	X1			3.44	High
Belief in increased productivity	(X1.1)	2	5	3.84	High
Belief in cost reduction	(X1.2)	1	5	3.02	Enough
Belief in environmental impact	(X1.3)	1	5	3.45	High
Subjective Norm	X2			2.73	Enough
Family support	(X2.1)	1	5	3.05	Enough
Other farmers recommendations	(X2.2)	1	5	2.41	Low
Government encouragement	(X2.3)	1	5	2.74	Enough
Perceived Behavioral Control	X3			2.73	Enough
Availability of resources	(X3.1)	1	5	2.47	Low
Confidence to operate technology	(X3.2)	1	5	2.98	Enough
Intention	Y			2.66	Enough
Intend to try smart farming	(Y.1)	1	5	2.54	Low
Plan to use smart farming	(Y.2)	1	5	2.77	Enough

Source: Primary Data, 2025

The results of the descriptive statistical analysis show that, in general, farmers in Kanigoro Village have a positive attitude towards the use of smart farming technology, with a mean score of 3.44, which falls into the 'high' category. Meanwhile, the subjective norm is in the 'moderate' category

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with a mean score of 2.73, indicating that social influence from family, other farmers, and the government is not yet a strong driver for technology adoption. Perceived behavioral control is also in the 'moderate' category with a mean score of 2.73, reflecting that farmers feel moderately capable of accessing and using the technology, although enhanced technical support and training are still required. The intention variable has a mean score of 2.66, also falling into the 'moderate' category. This indicates that farmers' desire to try and integrate smart farming technology remains moderate, thus requiring a more intensive approach to encourage this intention to translate into actual behavior.

Evaluation of Measurement & Structural Models

The data in this study were analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method with the aid of WarpPLS software. The objective is to determine the influence of the variables Attitude, Subjective Norm, and Perceived Behavioral Control on farmers' Intention to adopt smart farming technology. The analysis was conducted in two primary stages: the evaluation of the measurement model (outer model) and the structural model (inner model), based on the Theory of Planned Behavior (TPB) framework. The results are expected to provide a comprehensive insight into the factors that influence technology adoption intention.

Table 3. Measurement & Structural Models

Variables	AVE	AVE^2	CR	CA	VIF	R^2	f^2	Q^2	Indicators	Loading Factors
X1	0.577	0.760	0.803	0.631	1.248		0.082		X1.1	0.766
									X1.2	0.819
									X1.3	0.964
X2	0.580	0.761	0.805	0.636	1.567		0.191		X2.1	0.823
									X2.2	0.716
									X2.3	0.824
X3	0.754	0.868	0.860	0.674	1.524		0.258		X3.1	0.842
									X3.2	0.772
Y	0.786	0.887	0.880	0.728		0.531		0.543	Y.1	0.742
									Y.2	0.730

Source: Primary Data, 2025

The analysis of the measurement model in this study demonstrates that all indicators for each latent variable—namely, Attitude, Subjective Norm, Perceived Behavioral Control, and Intention—fulfill the criteria for validity and reliability. The convergent validity results show that all indicators have loading factor values above 0.70 and AVE values greater than 0.50, indicating that the indicators effectively capture their respective constructs. Discriminant validity was also confirmed, as the square root of each construct's AVE exceeded its correlation with other constructs. Moreover, the reliability test results reveal that the Composite Reliability (CR) values for all variables are above 0.70 and Cronbach's Alpha (CA) values surpass 0.60, signifying good internal consistency of the research instrument. These findings are consistent with Mahattanakhun & Suvittawat (2023), who also reported that meeting the thresholds of AVE, CR, and CA is essential to ensure construct validity and reliability in behavioral intention research. Their study emphasized that reliable and valid measurement models strengthen the credibility of subsequent structural model testing, which aligns

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with the current research conclusion that the instrument is suitable for advancing to the structural model analysis.

The analysis of the structural model indicates that the developed model possesses excellent predictive quality and goodness-of-fit. The R-Square (R^2) result of 0.531 shows that the variables of Attitude, Subjective Norm, and Perceived Behavioral Control collectively explain 53.1% of the variance in farmers' intention to adopt smart farming technology. The f-Square test indicates that Perceived Behavioral Control has the largest effect size ($f^2 = 0.258$), followed by Subjective Norm ($f^2 = 0.191$) and Attitude ($f^2 = 0.082$). Q-Square (Q^2) value of 0.543 confirms that the model has strong predictive relevance for the dependent variable.

Table 4. Goodness of Fit Analysis

	APC	ARS	AARS	AVIF	AFVIF	GoF	SPR	RSCR	SSR	NLBCDR
Results	0.313	0.531	0.516	1.256	1.598	0.598	1.000	1.000	1.000	1.000

Source: Primary Data, 2025

Furthermore, the Goodness of Fit (GoF) value of 0.598 is categorized as large, which signifies that the model has an excellent overall fit for both its measurement and structural components. No multicollinearity issues were detected, as all Variance Inflation Factor (VIF) values are below the threshold of 3.3, and all path coefficients indicate positive and significant relationships. Overall, the structural model in this study is concluded to be robust, significant, and relevant for explaining farmers' intention to adopt smart farming technology.

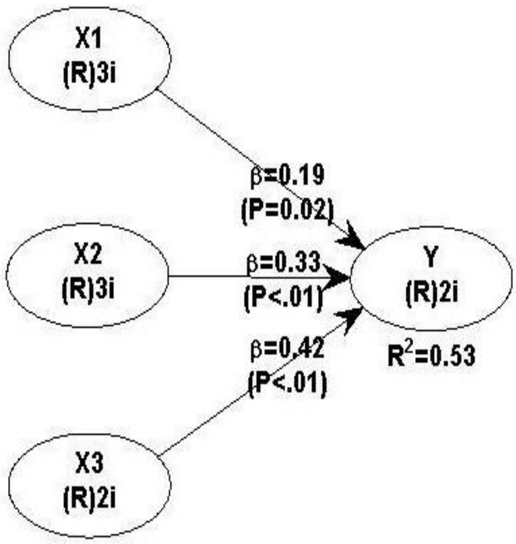

Figure 1. Path Coefficient

Hypothesis Analysis Results

Hypothesis testing in this study was conducted to determine the significant relationships and effects of the independent variables on the dependent variable. The statistical test, employing the PLS-SEM approach, was used to examine the magnitude of the path coefficients and the significance of each relationship between the variables.

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Table 5. Research Hypothesis

Hypothesis	Path Correlation	Path Coefficient	p-values	Results
H_1	X1 → Y	0.191	0.023	Significant
H_2	X2 → Y	0.329	< 0.001	Highly Significant
H_3	X3 → Y	0.420	< 0.001	Highly Significant

Source: Primary Data, 2025

The results of the hypothesis testing using PLS-SEM provide more than just statistical confirmation; they reflect the underlying dynamics of how farmers in Kanigoro Village form their intention to adopt smart farming technology. All three independent variables—Attitude, Subjective Norm, and Perceived Behavioral Control—were found to have a positive and significant influence, which indicates that farmers' adoption behavior is shaped not only by their personal evaluations but also by community pressures and their confidence in managing potential challenges. Specifically, Attitude had a significant effect with a path coefficient ($\beta = 0.191$, $p = 0.023$), showing that farmers who perceive smart farming as beneficial are more inclined to adopt it, although its effect is relatively modest compared to the other factors. Subjective Norm demonstrated a stronger role ($\beta = 0.329$, $p < 0.001$), suggesting that peer influence and social endorsement within farming communities weigh heavily on adoption decisions. Most notably, Perceived Behavioral Control emerged as the dominant factor ($\beta = 0.420$, $p < 0.001$), highlighting that the farmers' sense of capability and resource readiness is the strongest driver of adoption. Taken together, these results support all hypotheses and emphasize that while positive attitudes and social support matter, the decisive factor lies in whether farmers feel they truly have the means and capacity to adopt smart farming in practice.

The Influence of Attitude on Intention

From the perspective of the Theory of Planned Behavior (TPB), attitude represents the individual's evaluation of a behavior—whether it is perceived as beneficial or worthwhile. The present study confirms that farmers' attitudes toward smart farming technology have a positive and significant influence on their intention to adopt it ($\beta = 0.19$; $p = 0.023$). This suggests that farmers who perceive smart farming as capable of improving productivity, efficiency, and environmental outcomes are more inclined to adopt it, aligning Wilheppi et al. (2023) with TPB's assertion that favorable evaluations enhance behavioral intention.

However, when compared with the other predictors—Subjective Norm ($\beta = 0.33$) and Perceived Behavioral Control ($\beta = 0.42$)—the influence of attitude is the weakest. This implies that a positive attitude alone does not guarantee adoption; it must be reinforced by social validation and a sense of capability. This pattern echoes findings by Retnaningtyas et al. (2024) and Nugraha et al. (2024), who also reported that attitude tends to have a smaller effect relative to other TPB components. In the context of Kanigoro Village, this weaker influence may stem from the respondents' demographic characteristics—mostly older, less educated farmers with limited exposure to technology—who may not yet fully grasp the tangible benefits of smart farming. Unlike Xiang & Guo (2023), who found attitude to be a dominant factor when training and exposure were intensive, the present findings suggest that without such reinforcement, positive attitudes remain superficial. Thus, following Mishra et al. (2024), strengthening farmers' attitudes requires hands-on

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approaches—such as field demonstrations and continuous mentoring—to transform abstract appreciation into committed intention.

The Influence of Subjective Norm on Intention

In TPB, subjective norm reflects the perceived social pressure to perform or not perform a behavior. The results show that this variable exerts a strong and significant influence on farmers' intention to adopt smart farming ($\beta = 0.33$; $p < 0.001$), ranking second after perceived behavioral control. This indicates that social context—family, peers, and institutional actors—plays a crucial role in shaping behavioral intention. Subjective norm represents the perceived social pressure to perform or not perform a behavior, which is particularly relevant in communities where collective decision-making dominates individual choice. In Kanigoro Village, most farmers are older and have low levels of formal education, leading them to rely more on advice and examples from trusted social actors such as family members, peers, and agricultural input sellers when evaluating new technologies. This pattern aligns with Waiswa et al. (2024) and Nugraha et al. (2024), who demonstrated that in traditional agricultural settings, social encouragement often substitutes for limited technical understanding, turning interpersonal trust into a key motivator for behavioral intention. The results therefore suggest that social influence functions as a compensatory mechanism, helping farmers reduce uncertainty about unfamiliar technologies and reinforcing the perceived legitimacy of adoption decisions within their social group.

However, the influence of subjective norm is not universal and can vary depending on social structure and generational context. Retnaningtyas et al. (2024) found that subjective norm had little impact on younger farmers' adoption of climate-smart agriculture, as they tend to make more autonomous and information-driven decisions. This contrast underscores that in the Kanigoro context—where community bonds are strong and intergenerational influence remains dominant—social approval continues to play a decisive role in forming behavioral intention. Therefore, strengthening subjective norm requires interventions that go beyond traditional information delivery, focusing instead on social reinforcement strategies such as family-inclusive extension programs, peer-led training, and collaboration with local role models or farmer leaders. As also noted by Mishra et al. (2024), mobilizing social networks can transform external approval into intrinsic motivation, creating a more enduring intention to adopt smart farming technologies.

The Influence of Perceived Behavioral Control on Intention

According to TPB, perceived behavioral control (PBC) reflects the perceived ease or difficulty of performing a behavior. In this study, PBC emerged as the most powerful and significant predictor of intention ($\beta = 0.42$; $p < 0.001$), surpassing both attitude ($\beta = 0.19$) and subjective norm ($\beta = 0.33$). This demonstrates that the more confident farmers feel in their ability to access and operate smart farming tools, the stronger their intention to adopt the technology. The dominance of PBC underscores that adoption is not only a matter of belief or social influence but also of self-efficacy and resource readiness.

These results are consistent with Zamil et al. (2024) and Nugraha et al. (2024), who both identified PBC as the strongest determinant of adoption intention for agricultural technologies.

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However, Martínez-García et al. (2020) noted that when structural barriers—such as high costs and limited training—are perceived, the strength of PBC diminishes. This nuance resonates in Kanigoro Village, where uneven access to tools, training, and government support undermines farmers' perceived control. Critically, this finding suggests that behavioral intention cannot be strengthened solely through persuasion or awareness campaigns; it requires reducing real-world constraints. Therefore, empowering farmers through accessible technology packages, capacity-building programs, and continuous technical mentoring is vital to translate perceived control into actual adoption behavior.

Viewed collectively, the findings reaffirm the core logic of the Theory of Planned Behavior: intention is jointly shaped by evaluative (attitude), normative (subjective norm), and control (PBC) factors—but their influence is not equal. In Kanigoro Village, PBC ($\beta = 0.42$) stands as the dominant driver, followed by subjective norm ($\beta = 0.33$) and attitude ($\beta = 0.19$). This hierarchy reveals that while farmers conceptually value smart farming, their actual intention hinges more on whether they feel capable and socially supported to act on that belief. The analysis reflects that fostering adoption requires a simultaneous effort to strengthen positive attitudes, nurture supportive social environments, and, most crucially, remove external barriers that erode farmers' sense of control.

CONCLUSION AND SUGGESTION

The results of the PLS-SEM analysis in Kanigoro Village show that all three variables—attitude, subjective norm, and perceived behavioral control—positively and significantly influence farmers' intention to adopt smart farming technology. Attitude has a smaller yet significant effect ($\beta = 0.19$; $p = 0.023$), while subjective norm exerts a stronger influence ($\beta = 0.33$; $p < 0.001$), and perceived behavioral control emerges as the most dominant predictor ($\beta = 0.42$; $p < 0.001$). These findings affirm the Theory of Planned Behavior (Ajzen, 1991), highlighting that behavioral intention arises not only from favorable attitudes but also from strong social support and a sense of capability. Theoretically, the study extends TPB's applicability in explaining farmers' adoption behavior in developing contexts, while practically it underscores the need for policies that integrate technical training, social reinforcement, and improved access to user-friendly technologies to foster sustainable smart farming adoption.

To strengthen the adoption of smart farming technology, efforts should focus on enhancing farmers' understanding of its productivity and efficiency benefits through continuous training, field demonstrations, and cost-benefit case studies. Social influence, as reflected in the subjective norm component of the Theory of Planned Behavior, can be reinforced by involving families—particularly younger members—and farmer groups to build collective confidence in the technology. Equally important, strengthening farmers' perceived behavioral control requires not only providing affordable financing and consistent technical support but also designing user-friendly technologies that increase farmers' confidence in their ability to operate them. These strategies will collectively enhance positive attitudes, social support, and perceived capability, thereby fostering stronger and more sustainable intention to adopt smart farming practices among Indonesian farmers.

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REFERENCES

Ajzen, I. (2020). The Theory of Planned Behavior: Frequently Asked Questions. *Wiley*, *2*(4), 314–324. https://doi.org/10.1002/hbe2.195

Effendy, & Pratiwi, S. D. (2020). Tingkat Adopsi Teknologi Sistem Jajar Legowo Padi Sawah Di Kecamatan Cigasong Kabupaten Majalengka. *Jurnal Agrica Ekstensia*, *14*(1). https://doi.org/https://doi.org/10.55127/ae.v14i1.44

Kusumawati, E., Sutandi, A., Fuad, Moch. W. S., & Agustine, S. (2024). Peran Karakteristik Sosial-Ekonomi dalam Meningkatkan Kinerja Usaha Tani Sayur di Bandung. *Journal of Social Studies*, *5*(1), 61–69. https://doi.org/10.37010/fcs.v5i1.1505

Mahattanakhun, C., & Suvittawat, A. (2023). Perceived and Attitudes Influencing Intention to Adopt New Technology for Farm Production: A Case Study of Farmers at Nakhon Ratchasima Province Thailand. *International Journal of Professional Business Review*, *8*(5), e02111. https://doi.org/10.26668/businessreview/2023.v8i5.2111

Martínez-García, C. G., Maneul, C., Jordan, A., Rayas-Amor, A. A., Dorward, P., & Rehman, T. (2020). Understanding Factors Influencing Farmers' Intention for Adopting Improved Grassland Using the Theory of Reasoned Action, In the Highlands of Central Mexico. *IGC Proceedings*, *10*. https://uknowledge.uky.edu/igc/23/3-1-1/10

Ministry of Agriculture of Indonesia. (2023). Jaring, Cara Jitu Kendalikan Hama Burung Pipit. *Buletin Teknologi & Inovasi Pertanian*, *2*, 16–20.

Mishra, N., Bhandari, N., Maraseni, T., Devkota, N., Khanal, G., Bhusal, B., Basyal, D. K., Paudel, U. R., & Danuwar, R. K. (2024). Technology in Farming: Unleashing Farmers' Behavioral Intention for The Adoption of Agriculture 5.0. *PLoS ONE*, *19*(8). https://doi.org/10.1371/journal.pone.0308883

Nugraha, R., Muhaimin, A. W., Maulidah, S., Putri, R. W., & Maulidah, D. L. (2024). Fostering Food Security through Farmers' Intentions to Embrace Climate-Smart Agriculture: Unraveling the Impact of Attitude, Subjective Norms, and Behavioral Control. *IOP Conference Series: Earth and Environmental Science*, *1323*(1). https://doi.org/10.1088/1755-1315/1323/1/012018

Rachmawati, R. R. (2021). Smart Farming 4.0 Untuk Mewujudkan Pertanian Indonesia Maju, Mandiri, dan Modern. *Forum Penelitian Agro Ekonomi*, *38*(2), 137. https://doi.org/10.21082/fae.v38n2.2020.137-154

Ramdhan, M. (2021). *Metode Penelitian* (A. A. Effendy, Ed.). Cipta Media Nusantara.

Retnaningtyas, T. A., Padmaningrum, D., & Anantanyu, S. (2024). Perilaku Petani Milenial Provinsi Jawa Barat dalam Penerapan Climate-Smart Agriculture (CSA) pada Tanaman Hortikultura. *Jurnal Ilmiah Membangun Desa Dan Pertanian*, *9*(2), 160–171. https://doi.org/10.37149/jimdp.v9i2.1105

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http://ejournal2.undip.ac.id/index.php/agrisocionomics
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Ridwan, M., Wijayanti, A., Satiti, R., Santoso, T. B., Dutono, T., Suparno, H. W., Siswandari, N. A., Puspitorini, O., Kurniayajaya, M., Nisa, K., Lestari, P. E. W., Fatimah, Falsafah, T., & Saifulloh, M. K. (2023). Implementasi Si-Tani (Smart Irigasi Petani) Sebagai Inovasi Smart Farming 4.0 Untuk Pertanian Di Wilayah Pedesaan. *Jurnal Budimas*, *5*(1). https://doi.org/http://dx.doi.org/10.29040/budimas.v5i1.7084

Sawaluddin, M. R., & Lidayanti, S. (2024). Pencegahan DBD dengan Penyuluhan Hidup Bersih dan Sehat di Kecamatan Tawang Tasikmalaya Jawa Barat. *PROFICIO: Jurnal Pengabdian Kepada Masyarakat*, *5*(2), 920–932. https://doi.org/https://doi.org/10.36728/jpf.v5i2.3767

Waiswa, D., Muriithi, B. W., Murage, A. W., Ireri, D. M., Maina, F., Chidawanyika, F., & Yavuz, F. (2024). The Role of Social-Psychological Factors in the Adoption of Push-Pull Technology by Small-scale Farmers in East Africa: Application of the Theory of Planned Behavior. *Heliyon*, e41449. https://doi.org/10.1016/j.heliyon.2024.e41449

Wilheppi, R., Noer, M., & Syarfi, I. W. (2023). Persepsi Petani Terhadap Teknologi Smart Farming Dalam Pertanian Padi Sawah di Kabupaten Pasaman Barat. *Journal of Agribusiness and Community Empowerment (JACE)*, *6*(2), 103–110. https://doi.org/10.32530/jace.v6i2.67

Xiang, P., & Guo, J. (2023). Understanding Farmers' Intentions to Adopt Pest and Disease Green Control Techniques: Comparison and Integration Based on Multiple Models. *Sustainability (Switzerland)*, *15*(14). https://doi.org/10.3390/su151410822

Zamil, A. M. A., Javed, H. M. U., & Ali, S. (2024). Internet of Things Platforms Adoption in Agriculture: Comparative Theoretical Models. *International Journal of Retail and Distribution Management*. https://doi.org/10.1108/IJRDM-10-2022-0420