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Hybrid Agricultural Extension and Climate-Smart Practice Adoption: Evidence from Indonesian Rice Farmers

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ABSTRACT

Agricultural extension plays a pivotal role in promoting the adoption of climate-smart practices among smallholders, yet its effectiveness in Indonesia remains uneven amid structural constraints and rapid digital transformation. This study examines how extension information quality and trust in agents influence farmer learning outcomes and subsequent adoption of climate-smart practices, while testing the moderating effects of chat-app microlearning exposure and extension agent digital capability. A cross-sectional survey of 378 irrigated rice farmers in Central Java and East Nusa Tenggara provinces was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results show that information quality and trust significantly enhance knowledge gain and self-efficacy, which in turn foster positive attitudes, stronger adoption intentions, and early adoption behavior. Both chat-app microlearning and agent digital capability strengthen these psychological pathways, demonstrating the effectiveness of hybrid extension systems that combine interpersonal trust with digital reinforcement. Practically, the study suggests that co-designed hybrid advisory calendars, localized micro-videos, and digital-skills training for extension agents can enhance learning and inclusivity, while asynchronous SMS and radio-based materials can support regions with limited connectivity. These insights provide a framework for implementing Indonesia's Digital Agriculture Roadmap 2023–2045 and advancing inclusive, technology-enabled agricultural innovation.

Keywords: Agricultural extension, Climate-smart practices, Indonesia, Self-efficacy, Microlearning, Digital capability

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INTRODUCTION

Agriculture is central to achieving the global goals of food security, climate resilience and sustainable development. As climate variability intensifies, smallholder farmers who contribute over one-third of the world's food supply face escalating challenges related to drought, flooding, pest outbreaks, and market volatility (Touch et al., 2024). The international response has been the promotion of Climate-Smart Agriculture (CSA), defined as an integrated approach to sustainably increase productivity, enhance resilience, and reduce greenhouse gas emissions (Abbasi et al., 2022). Globally, more than 70 countries have incorporated CSA into their national agricultural plans, reflecting its status as a cornerstone of climate adaptation and mitigation strategies (Isnaeni Fathonah & Mashilal, 2021). Yet, the successful implementation of CSA depends not only on technical innovation but also on social and cognitive processes facilitated through agricultural extension.

Across regions, extension systems are evolving toward hybrid models that combine face-to-face interactions with digital tools to improve information dissemination and farmer engagement. Recent syntheses suggest that hybrid extension can enhance learning retention and behavioral change by reinforcing traditional advisory methods with mobile-based microlearning and peer exchange (Coggins et al., 2025; Sen et al., 2025). These systems are

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increasingly powered by artificial intelligence, chat applications and short-form digital media that enable continuous, contextual learning among dispersed farming communities (High et al., 2025). However, as digitalization advances, disparities in digital literacy among extension agents and farmers threaten to widen the knowledge and adoption gap, especially in lower-middle-income countries.

In Indonesia, where agriculture employs roughly 29% of the labor force and rice remains the dominant crop, CSA is now integral to the national climate agenda. Indonesia ranks among the top five rice-producing countries globally, with over 10.5 million hectares of rice fields yielding approximately 54 million tons of unmilled rice in 2023 (Isnaeni Fathonah & Mashilal, 2021). Yet, the sector faces mounting vulnerability due to extreme weather, soil degradation, and aging infrastructure. Extension services, though extensive, struggle to maintain effectiveness: as of 2023, Indonesia had approximately 46,000 active extension agents serving over 18 million farmers, an average ratio exceeding 1:390 (Dewi et al., 2025). This imbalance constrains personalized guidance and limits agents' capacity to monitor CSA adoption. Moreover, only about 45% of field officers report confidence in using digital platforms to support extension delivery (Sugihono et al., 2024).

Despite these constraints, digital transformation in rural Indonesia has accelerated rapidly. Over 70% of rural households now own smartphones and messaging applications especially WhatsApp are widely used for sharing agricultural advice and coordinating group activities (Syafi'i & Anang Anas Azhar, 2025). This digital engagement has created fertile ground for chat-app microlearning, where farmers exchange short videos, field photos, and localized tips that reinforce formal training sessions. These dynamics illustrate how informal, peer-driven knowledge ecosystems can complement formal extension structures and reduce informational asymmetries between farmers and agents.

However, significant knowledge gaps remain in understanding how hybrid extension mechanisms drive behavioral change. First, prior research often treats extension exposure as a direct predictor of adoption, overlooking the psychological mechanisms particularly knowledge gain and self-efficacy that mediate the relationship between advisory quality and adoption (Balenzano et al., 2018; Kegode et al., 2025). Second, evidence on digital reinforcement via chat-app microlearning remains limited, especially regarding its capacity to enhance learning and confidence in Southeast Asian smallholder contexts. Third, there is little empirical analysis of how extension agents' digital capability moderates the effectiveness of information delivery and trust formation (Makamane et al., 2025). Understanding these multi-layered dynamics is crucial for designing inclusive, scalable, and technologically enabled extension systems aligned with Indonesia's digital agriculture roadmap.

The theoretical foundation of this study builds upon information quality theory, social cognitive theory, and technology adoption models to explain how agricultural extension influences the adoption of climate-smart practices. Information quality theory emphasizes that farmers' evaluation of advice depends on its accuracy, reliability, completeness, and timeliness, which in turn shapes their willingness to act upon it (Danjumah et al., 2024). In the Indonesian context, where diverse agroecological conditions require locally adapted information, the quality of extension messages is essential for reducing uncertainty and guiding decisions (Løhre et al., 2024). At the same time, social cognitive theory highlights that adoption is not only a matter of information but also of self-efficacy, defined as an individual's belief in their capacity to perform specific actions (Sun et al., 2024). Extension interactions that strengthen knowledge also build confidence, which in turn promotes favorable attitudes and greater behavioral intention to adopt new practices (Cordova et al., 2014). These psychological mechanisms help to explain why trust in extension agents, reflecting perceptions of competence, integrity, and benevolence, is a critical determinant of adoption outcomes. Complementing these perspectives, technology adoption models such as the Technology Acceptance Model and the Theory of Planned Behavior demonstrate that attitudes and intentions are reliable predictors of adoption, while contextual conditions such as facilitating infrastructure or digital tools may moderate these pathways (Venkatesh et al., 2012; Wei et al., 2025). In Indonesia, emerging evidence shows that farmers increasingly rely on WhatsApp groups and other chat applications to receive short videos and peer support, while the digital capability of extension agents affects the effectiveness of hybrid extension delivery (Thapa et al., 2025). Taken together, these theoretical perspectives provide a coherent rationale for the proposed framework, which positions information quality and trust as antecedents of knowledge gain and self-efficacy, emphasizes attitudes and intentions as mediators of early adoption, and introduces digital channels and agent capability as moderators that capture contemporary transformations in Indonesian extension systems (Fig. 1).

Extension Information Quality and Farmer Learning

Extension information quality is widely recognized as a decisive factor in shaping learning outcomes among farmers (Kang & Namkung, 2019). High-quality information is typically defined as accurate, reliable, complete, and timely, enabling recipients to process messages effectively and apply them in practice (Kang & Namkung, 2019). Within agricultural extension, the delivery of clear and trustworthy information is essential for reducing uncertainty about new technologies and for helping farmers evaluate both benefits and risks (Abiri et al., 2023). When farmers receive advice that is consistent, relevant to their local context, and free from ambiguity, they are more likely to assimilate new knowledge about climate-smart practices, including water-saving methods, organic fertilization, and integrated pest management (Banda et al., 2024). Evidence from smallholder contexts shows that reliable extension messages enhance understanding and reduce misperceptions, which in turn increases confidence in adopting sustainable innovations (Sun & Lu, 2023).

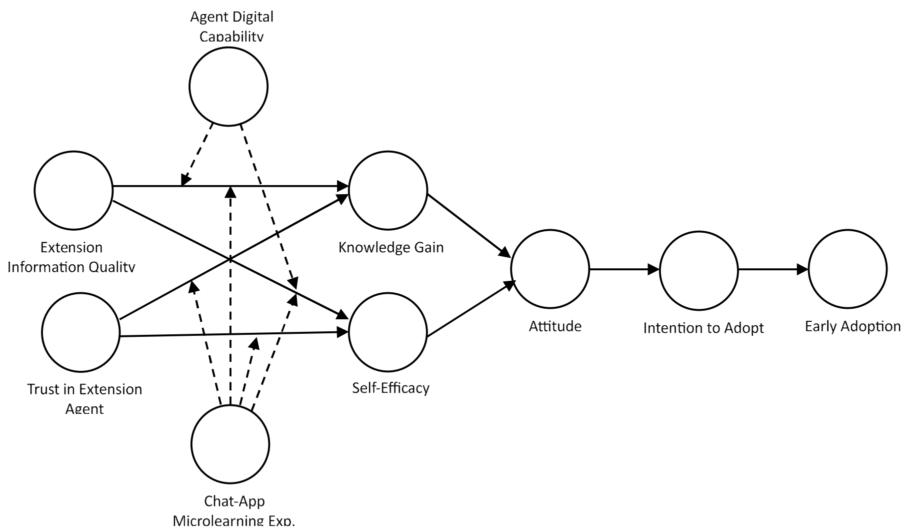

Fig. 1: Research Framework.

The influence of information quality extends beyond knowledge acquisition to farmers' self-belief in their ability to act. According to social cognitive theory, self-efficacy emerges not only from personal experience but also from access to credible information that guides action (Capron Puozzo & Audrin, 2021). When extension services provide detailed and trustworthy recommendations, farmers perceive that they can successfully implement new techniques under local conditions, thereby increasing their sense of control and capability. Conversely, inconsistent or low-quality advice undermines confidence and may discourage experimentation. Thus, the provision of high-quality extension information is expected to strengthen both knowledge gain and self-efficacy in the adoption of climate-smart practices.

H1: Extension information quality positively influences knowledge gain.

H2: Extension information quality positively influences self-efficacy.

Trust in Extension Agents and Farmer Learning

Trust in extension agents is a critical factor that shapes how farmers interpret and act upon agricultural advice. Trust is commonly understood as the perception that an agent demonstrates competence, integrity, and benevolence, and therefore acts in the best interests of the farmer (Dixon et al., 2024). In contexts where farmers face significant risks and uncertainties, particularly when experimenting with new climate-smart practices, the credibility of the source is often as important as the content of the information itself (Lucassen & Schraagen, 2013). When farmers believe that extension agents are knowledgeable, honest, and genuinely committed to their welfare, they are more likely to engage with the advice, seek clarification, and internalize the knowledge (Gao et al., 2024).

Beyond knowledge acquisition, trust also fosters confidence to act. Social cognitive theory suggests that observational learning and verbal persuasion are central to building self-efficacy (Gao et al., 2024). Trusted extension agents are more persuasive, as farmers are inclined to accept their guidance as both feasible and contextually appropriate. This assurance reduces the perceived risks of trying new practices and strengthens farmers' belief that they can successfully implement them. Empirical studies have shown that trust in advisory services increases both the understanding of innovations and the confidence to adopt them, underscoring the pivotal role of relational quality in extension systems (Cao et al., 2025). In Indonesia, where extension officers often serve as long-term interlocutors between government programs and rural communities, trust becomes a vital mechanism for translating information into concrete adoption behavior (Dewi et al., 2025).

H3: Trust in extension agents positively influences knowledge gain.

H4: Trust in extension agents positively influences self-efficacy.

Knowledge Gain and Self-efficacy Shaping Attitude

Knowledge gained from extension services plays a fundamental role in shaping farmers' evaluations of agricultural innovations. When farmers acquire new and accurate information, they are better able to understand the relative advantages, costs, and risks associated with climate-smart practices, which leads to more favorable attitudes toward adoption (Kangogo et al., 2021). Improved knowledge reduces uncertainty, clarifies misconceptions, and enables farmers to weigh the long-term benefits of practices such as water management, organic fertilization, and integrated pest control against short-term constraints (Maffia et al., 2025). Empirical studies across smallholder contexts consistently show that knowledge is a precursor to attitudinal change, as informed farmers are more likely to develop positive perceptions of sustainability-oriented technologies (Azmi et al., 2024).

In addition to knowledge, self-efficacy is a critical psychological resource that reinforces positive evaluations of new practices. Farmers who believe in their ability to implement climate-smart methods are more likely to view these practices as manageable, beneficial, and aligned with their farming systems. Social cognitive theory emphasizes that confidence in one's capacity to act not only motivates behavior but also influences how individuals appraise potential innovations (Sun et al., 2024). Studies in agricultural adoption confirm that higher self-efficacy strengthens favorable attitudes toward innovations, thereby increasing the likelihood of eventual uptake (Luo et al., 2024). In Indonesia, where resource constraints and climate variability can discourage experimentation, self-efficacy becomes especially vital in turning technical knowledge into supportive attitudes that underpin adoption decisions.

H5: Knowledge gain positively influences attitude toward climate-smart practices.

H6: Self-efficacy positively influences attitude toward climate-smart practices.

Attitude, Intention and Adoption Behavior

Attitudes are central determinants of behavior in most models of innovation adoption. The Theory of Planned Behavior and the Technology Acceptance Model (Wei et al., 2025) both argue that favorable evaluations of an innovation create the psychological foundation for forming behavioral intentions. In agricultural contexts, positive attitudes toward climate-smart practices signal that farmers perceive these practices as beneficial, relevant, and feasible, which in turn drives their willingness to adopt them (Johnson et al., 2023). When farmers develop supportive attitudes through enhanced knowledge and self-efficacy, they are more likely to express an intention to implement the practices in the near future, making intention a reliable predictor of subsequent behavior (Erekalo et al., 2025).

Intention alone, however, does not guarantee change unless it translates into concrete actions. Technology adoption studies consistently confirm that intention is the strongest antecedent of actual adoption, reflecting the farmer’s readiness to invest time, labor and resources in trying a new practice (Feisthauer et al., 2024; Venkatesh et al., 2012). In the Indonesian setting, where smallholders face constraints such as limited capital and high-risk exposure, intention functions as a critical intermediate step that signals motivation to trial climate-smart methods despite uncertainty. The sequential process from favorable evaluation to expressed intention and finally to trial adoption therefore aligns with both theoretical expectations and empirical evidence.

H7: Attitude positively influences intention to adopt climate-smart practices.

H8: Intention positively influences early adoption of climate-smart practices.

Moderation by Chat-App Microlearning Exposure

The increasing use of mobile chat applications such as WhatsApp has transformed the way farmer’s access and share agricultural knowledge. Digital microlearning through chat groups provides short videos, images, and peer discussions that complement formal extension delivery (Rof et al., 2024). Such platforms enhance the accessibility and timeliness of information, allowing farmers to revisit content, clarify doubts with peers, and exchange experiential knowledge. When farmers are exposed to these digital learning channels, the effectiveness of extension services is likely to increase because information becomes more salient, contextualized, and reinforced (Sen et al., 2025).

In particular, chat-app (CA) exposure is expected to strengthen the link between extension information quality and farmer learning outcomes. When high-quality advice is shared or discussed in digital groups, farmers can repeatedly engage with the content, verify its reliability with peers, and thus gain deeper knowledge of climate-smart practices (Rodríguez-Barillas et al., 2024). Similarly, chat-app mediated discussions can enhance the persuasiveness of trusted agents by allowing farmers to witness peer validation of the advice, thereby improving both knowledge gain and self-efficacy. In this way, digital interaction does not replace traditional extension but rather magnifies its effect through continuous reinforcement.

H9a: Chat-app microlearning exposure strengthens the positive effect of extension information quality on knowledge gain.

H9b: Chat-app microlearning exposure strengthens the positive effect of trust in extension agents on knowledge gain.

H9c: Chat-app microlearning exposure strengthens the positive effect of extension information quality on self-efficacy.

H9d: Chat-app microlearning exposure strengthens the positive effect of trust in extension agents on self-efficacy.

Moderation by Extension Agent Digital Capability

The effectiveness of agricultural extension increasingly depends on the ability of agents to integrate digital tools into their advisory work (High et al., 2025). Extension agent digital capability refers to the skills and confidence of field officers in using information and communication technologies to deliver advice, curate content, and interact with farmers (Ngulube, 2025). When agents are digitally capable, they can translate high-quality information into more accessible formats, such as visual demonstrations, short videos, or interactive discussions, thereby making the advice more understandable and actionable (Dwivedi et al., 2021). Conversely, low digital capability may limit the practical impact of otherwise reliable information, as poor presentation or delivery reduces farmers’ comprehension and engagement.

Farmer perceptions of agent digital capability therefore condition the extent to which information quality translates into learning outcomes. If farmers observe that extension agents effectively use digital platforms to communicate complex ideas, they are more likely to deepen their knowledge of climate-smart practices and believe that they can apply these methods in their own fields (Sarku et al., 2025). This confidence reinforces the pathway from information quality to self-efficacy, ensuring that credible advice is not only understood but also perceived as feasible to implement in practice.

H10a: Extension agent digital capability strengthens the positive effect of extension information quality on knowledge gain.

H10b: Extension agent digital capability strengthens the positive effect of extension information quality on self-efficacy.

Against this background, this study investigates how extension information quality and trust in agents influence Indonesian rice farmers' adoption of climate-smart practices through the mediating mechanisms of knowledge gain, self-efficacy, and attitudes. It further examines whether chat-app microlearning exposure and perceived agent digital capability strengthen these pathways. A prediction-oriented partial least squares structural equation modeling (PLS-SEM) approach is applied to evaluate both the theoretical and predictive validity of the proposed framework.

This research makes three key contributions. First, it advances global debates on agricultural extension by explicitly modeling the psychological mechanisms that translate information and trust into behavioral change. Second, it extends the literature on digital and hybrid extension by testing how microlearning and agent capability condition these mechanisms in a developing-country context. Third, it provides Indonesia-specific empirical evidence for policymakers designing integrated extension strategies that combine conventional and digital elements. Collectively, these insights contribute to the international effort to build resilient, inclusive, and digitally empowered extension systems capable of accelerating CSA adoption and supporting smallholder adaptation to climate change.

MATERIALS & METHODS

This study employed a quantitative, cross-sectional survey design to examine the relationships between extension information quality, trust in extension agents, knowledge gain, self-efficacy, attitude, adoption intention, and early adoption of climate-smart practices among Indonesian rice farmers. The structural model incorporated two moderators chat-app (CA) microlearning exposure and extension agent digital capability and was estimated using Partial Least Squares Structural Equation Modeling (PLS-SEM). A prediction-oriented analytical approach was followed, consistent with the rationale for PLS-SEM in exploratory and theory-extension contexts (Hair et al., 2024).

The target population comprised irrigated rice farmers in two provinces of Indonesia: Central Java and East Nusa Tenggara, which represent contrasting agricultural and institutional contexts. Central Java illustrates a region with relatively developed extension services and higher input accessibility, whereas East Nusa Tenggara typifies more resource-constrained extension environments. The study areas are shown in Fig. 2, which presents the two provinces, the sampled sub-districts with active extension posts, and the approximate locations of participating farmer groups. A two-stage cluster sampling procedure was implemented. In the first stage, six sub-districts with active extension centers were purposively selected in each province to capture regional diversity in extension performance and agroecological conditions. In the second stage, farmer groups within those sub-districts were randomly selected, and lists of active members served as the sampling frame for household interviews.

Inclusion criteria required that respondents (a) had cultivated rice during the most recent growing season, (b) had received extension advice or interacted with an extension agent or digital platform within the previous twelve months, and (c) were willing to provide informed consent. Replacement rules were applied when selected individuals were unavailable after two contact attempts or no longer engaged in rice farming; in such cases, the next eligible farmer on the list was invited. The final sample comprised 378 valid responses collected between March and May 2024.

Respondents were demographically diverse: 64.3% were male and 35.7% female, with a mean age of 44.2 years. Average farm size was 0.74 hectares, and most respondents had completed at least junior secondary education.

All constructs in this study were modeled as reflective, consistent with the theoretical assumption that the observed indicators represent manifestations of underlying latent variables rather than formative causal components.

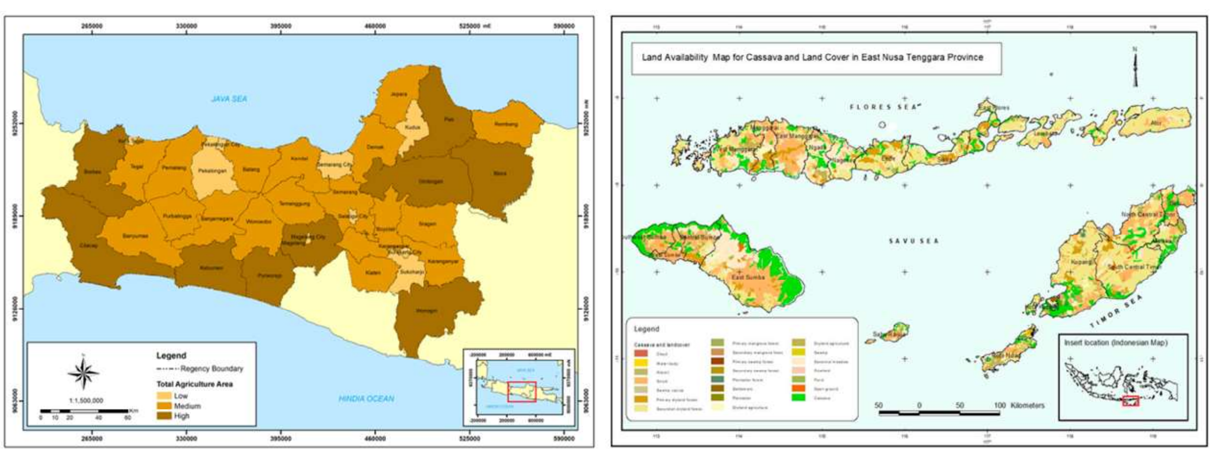

Fig. 2: Research Locations; Source: Ngongo et al. (2022) and Putri et al., 2020).

The survey instrument consisted of nine multi-item latent constructs measured on seven-point Likert scales (1=strongly disagree, 7=strongly agree). Items were adapted from validated instruments (Table 1) and encompassed extension information quality, trust in agents, knowledge gain, self-efficacy, attitude toward climate-smart practices, adoption intention, early adoption, chat-app microlearning (CA) exposure, and agent digital capability. The questionnaire was pre-tested with thirty farmers in West Java to ensure linguistic clarity and contextual appropriateness. Minor revisions were made based on feedback before the full survey.

Data collection was conducted through face-to-face interviews at farmers' homes or local group meeting points by trained enumerators experienced in agricultural surveys. A two-day training session familiarized enumerators with study objectives, questionnaire administration, and ethical protocols. Participation was voluntary, informed consent was obtained, and confidentiality was assured. To mitigate social desirability bias, respondents were reminded that the study was independent of government programs and that their answers would have no administrative consequences.

Common-method bias (CMB) was controlled both procedurally and statistically. Procedural safeguards included anonymity assurance, varying scale anchors, and the separation of conceptually related items. Post-hoc tests confirmed minimal bias: Harman's single-factor test showed the first factor accounted for only 29.6% of variance, well below the 50% threshold; all full-collinearity variance inflation factors (VIFs) were below 3.3, satisfying Kock (2015) criterion.

Data were analyzed using SmartPLS 4 (build 4.0.9) following a two-stage Partial Least Squares Structural Equation Modeling (PLS-SEM) procedure. In the first stage, the measurement model was evaluated to ensure that each construct was measured reliably and validly. Indicator reliability, internal consistency, and convergent validity were assessed in accordance with established PLS-SEM guidelines to confirm that the observed indicators accurately represented their respective latent variables. Discriminant validity was then examined using both the heterotrait–monotrait (HTMT) ratio and an inspection of cross-loadings to verify that each construct was empirically distinct. These assessments collectively ensured that the reflective measurement model met accepted methodological standards for construct validity and reliability prior to testing the structural relationships among variables.

The structural model was then tested for collinearity, significance, and explanatory power. Multicollinearity diagnostics confirmed all inner VIFs < 3.3, indicating absence of redundancy among predictors. Path coefficients were estimated via the PLS algorithm (maximum iterations=300; stop criterion=1×10^{-7}). Statistical significance was assessed using bootstrapping with 5,000 resamples, bias-corrected confidence intervals, and two-tailed tests at $P<0.05$. Model adequacy was evaluated using the standardized root mean square residual (SRMR) and normed fit index (NFI), with cut-offs of ≤ 0.08 and ≥ 0.90, respectively.

Appendix Table 1: Measurement items for each construct

Construct	Item	Source
Extension Information Quality	IQ1. The information I receive from extension agents is accurate. IQ2. The information is complete and covers what I need to know. IQ3. The information is reliable and consistent across messages. IQ4. The information is timely for my farming activities. IQ5. The information is objective and free from bias.	Adapted from Danjumah et al. (2024); Lee et al. (2002)
Trust in Extension Agents	TR1. I believe extension agents are competent in providing agricultural advice. TR2. I believe extension agents act with integrity when dealing with farmers. TR3. Extension agents care about the well-being of farmers. TR4. I trust extension agents to recommend practices that benefit me.	Adapted from Mayer et al. (1995); Meijer et al. (2015)
Knowledge Gain	KG1. I have learned new farming techniques from extension services. KG2. I have improved my understanding of climate-smart practices. KG3. I can now better evaluate the benefits and risks of sustainable methods. KG4. I know more about specific practices such as water management or pest control.	Adapted from Erekalo et al. (2025); Meijer et al. (2015)
Self-Efficacy	SE1. I am confident I can apply the recommended practices on my farm. SE2. I can overcome challenges when implementing new farming methods. SE3. Even if resources are limited, I can still try new practices. SE4. I believe I can successfully manage the risks of adopting new methods.	Adapted from Bandura, (1997); Wuepper et al. (2020)
Attitude toward Climate-Smart Practices	AT1. Using climate-smart practices is a good idea for my farm. AT2. Climate-smart practices are beneficial for my productivity. AT3. Overall, I have a positive evaluation of climate-smart practices.	Adapted from Ajzen (1991); Erekalo et al. (2025)
Adoption Intention	IN1. I intend to adopt climate-smart practices in the next season. IN2. I plan to apply these practices on a significant part of my farm. IN3. I am willing to invest resources to adopt climate-smart practices.	Adapted from Davis, (1989); Venkatesh et al. (2012)
Early Adoption	EA1. I have already tried one or more climate-smart practices this season. EA2. I currently use these practices on part of my farmland. EA3. I expect to continue applying these practices in future seasons.	Adapted from Erekalo et al. (2025)
Chat-App Microlearning Exposure	CA1. I frequently receive farming information through WhatsApp or similar groups. CA2. I discuss agricultural practices with peers in chat groups. CA3. I watch short videos on farming techniques shared through chat apps. CA4. I often rely on chat apps to clarify extension information.	Adapted from Coggins et al. (2025)
Extension Agent Digital Capability	DC1. Extension agents in my area are skilled in using digital tools for advice. DC2. Extension agents effectively share information through mobile or online platforms. DC3. Extension agents are capable of creating or forwarding farming videos or images. DC4. Extension agents are confident in using digital communication with farmers.	Adapted from Sugihono et al. (2024)

Predictive relevance was examined through the blindfolding procedure (omission distance=7), and out-of-sample predictive power was evaluated using the PLSpredict algorithm with ten-fold cross-validation and root mean square error (RMSE) comparison against linear regression benchmarks. Lower Q^2predict and RMSE values relative to linear models indicated higher predictive validity.

Missing data were minimal (< 2% per item) and were treated using pairwise deletion, as recommended for PLS-SEM when data are missing completely at random. No outliers were detected beyond ± 3 standard deviations.

Moderation effects for chat-app microlearning (CA) exposure and extension agent digital capability were tested using the product-indicator approach with mean-centered variables to reduce multicollinearity. Interaction terms were evaluated using the same bootstrapping configuration to determine whether digital reinforcement significantly strengthened the relationships between extension information quality, trust, and psychological learning outcomes.

RESULTS

Descriptive Statistics

The descriptive statistics presented in Table 2 reveal that most constructs scored above the midpoint of the seven-point Likert scale, suggesting generally favorable perceptions among Indonesian rice farmers. Extension information quality (M=5.32) and knowledge gain (M=5.41) were rated highly, indicating that farmers perceived the advice received from extension services as both credible and informative. Similarly, attitudes toward climate-smart practices (M=5.47) and adoption intention (M=5.36) were relatively strong, reflecting positive evaluations and a willingness to implement sustainable farming methods. These findings highlight the potential for extension services to influence psychological mechanisms that precede adoption decisions.

Table 2: Descriptive statistics of the constructs (N=378)

Construct	Mean	Standard Deviation	Minimum	Maximum
Extension Information Quality	5.32	0.91	1	7
Trust in Extension Agents	5.18	0.87	1	7
Knowledge Gain	5.41	0.88	1	7
Self-Efficacy	5.09	0.94	1	7
Attitude toward Climate-Smart Practices	5.47	0.85	1	7
Adoption Intention	5.36	0.93	1	7
Early Adoption	4.92	1.01	1	7
Chat-App Microlearning Exposure	4.85	1.12	1	7
Extension Agent Digital Capability	4.67	1.05	1	7

Note. Items were measured on a seven-point Likert scale (1=strongly disagree, 7=strongly agree).

At the same time, the lower mean for early adoption (M=4.92) compared with intention suggests a gap between expressed willingness and actual practice. This discrepancy may be explained by resource limitations, risk considerations, or uneven access to inputs, which are well-documented barriers in smallholder contexts. Moderating constructs such as chat-app microlearning exposure (M=4.85) and extension agent digital capability (M=4.67) were rated at more moderate levels, reflecting that while digital tools are increasingly used, their integration into extension systems remains incomplete. Overall, the results from Table 2 provide initial evidence that while farmers are receptive to climate-smart practices, the challenge lies in converting intention into concrete adoption behaviors.

Measurement Model

The reliability and validity assessment summarized in Table 3 indicates that the measurement model met established quality criteria for PLS-SEM. All indicators demonstrated strong loadings on their respective constructs, confirming that each item meaningfully represented the underlying latent variable. The reliability coefficients showed satisfactory internal consistency, and the extracted variance values confirmed adequate convergent validity across all constructs. Collectively, these results affirm that the measurement items used in this study effectively captured the intended dimensions of extension information quality, trust, psychological mechanisms, and adoption outcomes within the hybrid agricultural extension framework.

Table 3: Factor loadings, reliability, and validity results

Construct	Code	Loading	Cronbach's	CR	AVE
Extension Information Quality	IQ1	0.82	0.88	0.91	0.67
	IQ2	0.84			
	IQ3	0.87			
	IQ4	0.80			
	IQ5	0.79			
Trust in Extension Agents	TR1	0.85	0.87	0.91	0.71
	TR2	0.88			
	TR3	0.83			
	TR4	0.81			
Knowledge Gain	KG1	0.83	0.88	0.92	0.73
	KG2	0.86			
	KG3	0.84			
	KG4	0.79			
Self-Efficacy	SE1	0.81	0.86	0.90	0.69
	SE2	0.85			
	SE3	0.83			
	SE4	0.78			
Attitude toward Climate-Smart Practices	AT1	0.87	0.85	0.90	0.76
	AT2	0.89			
	AT3	0.85			
Adoption Intention	IN1	0.86	0.86	0.91	0.77
	IN2	0.84			
	IN3	0.88			
Early Adoption	EA1	0.80	0.84	0.89	0.73
	EA2	0.83			
	EA3	0.85			
Chat-App Microlearning Exposure	CA1	0.82	0.85	0.89	0.67
	CA2	0.79			
	CA3	0.85			
	CA4	0.81			
Extension Agent Digital Capability	DC1	0.83	0.86	0.90	0.70
	DC2	0.86			
	DC3	0.82			
	DC4	0.80			

The discriminant validity assessment using the heterotrait–monotrait (HTMT) ratios is reported in Table 4. All HTMT values were well below the conservative threshold of 0.85, indicating that the constructs were empirically distinct from one another. The highest value was observed between knowledge gain and self-efficacy (0.70), which is theoretically expected given their conceptual proximity, yet still below the acceptable cutoff. The moderating constructs, chat-app microlearning exposure and extension agent digital capability showed moderate but distinct associations with other constructs, further supporting the argument that they represent unique dimensions of the hybrid extension framework. These findings confirm that the measurement model possessed adequate discriminant validity, allowing the structural relationships to be tested with confidence.

Table 4: Discriminant validity using HTMT criterion

Construct	1	2	3	4	5	6	7	8	9
Extension Information Quality	–								
Trust in Extension Agents	0.71	–							
Knowledge Gain	0.68	0.66	–						
Self-Efficacy	0.64	0.63	0.70	–					
Attitude toward Climate-Smart Practices	0.59	0.58	0.67	0.65	–				
Adoption Intention	0.56	0.55	0.63	0.62	0.72	–			
Early Adoption	0.52	0.50	0.58	0.59	0.61	0.69	–		
Chat-App Microlearning Exposure	0.48	0.46	0.52	0.51	0.49	0.47	0.45	–	
Extension Agent Digital Capability	0.50	0.49	0.54	0.53	0.51	0.50	0.48	0.60	–

The cross-loading matrix (Appendix 2) further confirmed the discriminant validity of the reflective measurement model. All indicators exhibited their highest loadings on their respective latent constructs, with standardized coefficients ranging between 0.74 and 0.89. These values exceed the recommended threshold of 0.70, indicating satisfactory indicator reliability (Hair et al., 2024). Non-target loadings were substantially lower, and the minimum loading difference between each indicator's intended construct and the next highest cross-loading exceeded 0.20, thereby satisfying the conservative discriminant validity criterion suggested in recent PLS-SEM literature.

Appendix 2 Table 4: Cross-Loadings of Measurement Items

Indicators	IQ	TRU	KG	SE	ATT	INT	EA	CM	DC
IQ1	0.84	0.52	0.56	0.48	0.44	0.39	0.37	0.33	0.35
IQ2	0.82	0.47	0.55	0.46	0.43	0.40	0.36	0.31	0.34
IQ3	0.86	0.49	0.58	0.50	0.47	0.44	0.41	0.35	0.36
IQ4	0.80	0.45	0.53	0.46	0.42	0.37	0.33	0.32	0.31
IQ5	0.83	0.50	0.57	0.48	0.45	0.40	0.38	0.36	0.34
TRU1	0.49	0.85	0.44	0.42	0.38	0.35	0.31	0.30	0.33
TRU2	0.52	0.88	0.48	0.45	0.41	0.37	0.34	0.29	0.32
TRU3	0.46	0.83	0.43	0.39	0.36	0.33	0.31	0.27	0.30
TRU4	0.44	0.69	0.41	0.36	0.34	0.30	0.29	0.25	0.27
KG1	0.57	0.48	0.81	0.64	0.55	0.47	0.44	0.41	0.43
KG2	0.53	0.45	0.83	0.62	0.57	0.49	0.46	0.42	0.45
KG3	0.55	0.43	0.85	0.63	0.58	0.50	0.47	0.40	0.42
KG4	0.51	0.41	0.80	0.60	0.54	0.47	0.43	0.38	0.40
SE1	0.48	0.44	0.63	0.82	0.59	0.51	0.47	0.42	0.43
SE2	0.46	0.42	0.61	0.84	0.57	0.50	0.45	0.41	0.42
SE3	0.47	0.43	0.62	0.85	0.59	0.52	0.49	0.44	0.45
SE4	0.44	0.39	0.58	0.81	0.55	0.48	0.44	0.39	0.41
ATT1	0.46	0.41	0.56	0.59	0.84	0.61	0.55	0.44	0.42
ATT2	0.45	0.39	0.55	0.57	0.85	0.62	0.56	0.46	0.43
ATT3	0.42	0.37	0.52	0.55	0.82	0.60	0.53	0.42	0.40
INT1	0.39	0.35	0.46	0.51	0.63	0.83	0.62	0.39	0.37
INT2	0.40	0.36	0.48	0.52	0.65	0.85	0.63	0.41	0.38
INT3	0.38	0.34	0.45	0.50	0.61	0.80	0.59	0.38	0.35
EA1	0.36	0.31	0.44	0.47	0.56	0.62	0.82	0.41	0.39
EA2	0.35	0.29	0.43	0.46	0.55	0.60	0.83	0.40	0.38
EA3	0.34	0.30	0.41	0.45	0.53	0.59	0.81	0.39	0.37
EA4	0.33	0.29	0.40	0.44	0.51	0.58	0.80	0.37	0.35
CM1	0.31	0.28	0.39	0.41	0.43	0.38	0.36	0.82	0.48
CM2	0.32	0.27	0.38	0.40	0.41	0.37	0.34	0.84	0.46
CM3	0.34	0.29	0.41	0.43	0.44	0.39	0.36	0.85	0.49
CM4	0.30	0.26	0.37	0.39	0.40	0.35	0.32	0.80	0.44
DC1	0.34	0.31	0.42	0.44	0.41	0.38	0.36	0.45	0.83
DC2	0.35	0.33	0.43	0.46	0.42	0.39	0.37	0.46	0.85
DC3	0.33	0.31	0.40	0.43	0.40	0.37	0.35	0.44	0.82
DC4	0.31	0.29	0.38	0.41	0.38	0.36	0.34	0.42	0.80

No evidence of problematic cross-loadings was observed. Two items (TRU4 and EA4) showed slightly lower loadings (0.69–0.70) relative to other indicators but were retained because they are theoretically essential for content coverage and their inclusion did not compromise composite reliability (CR > 0.85) or average variance extracted (AVE > 0.50). Their retention ensured the constructs captured the full conceptual range of perceived trust and early adoption behavior.

Table 5 presents the descriptive statistics and pairwise correlations among the latent constructs. The mean scores indicate generally favorable farmer perceptions across all variables, particularly regarding information quality, trust in extension agents, and attitudes toward climate-smart agriculture, while early adoption recorded a lower mean, reflecting a lag between behavioral intention and actual practice. The moderate standard deviations demonstrate adequate variability across responses, ensuring the robustness of subsequent structural estimation.

The correlation coefficients are uniformly positive and of moderate magnitude, implying that the constructs are conceptually related but not redundant. Stronger associations were observed between knowledge gain, self-efficacy, and attitude, consistent with social-cognitive interpretations of learning and behavioral readiness. The relatively weaker correlations involving chat-app microlearning exposure and agent digital capability suggest that these digital variables function as contextual enhancers rather than direct determinants of adoption behavior.

Structural Assessment

Table 6 summarizes the explanatory and predictive performance of the structural model. The R^2 and adjusted R^2 values indicate that the model accounts for moderate to substantial portions of variance across all endogenous constructs, with the highest explanatory power observed for adoption intention and attitude. These results confirm that the proposed framework effectively captures the cognitive, affective, and behavioral mechanisms underlying farmers' adoption of climate-smart agricultural practices.

The f^2 values demonstrate that information quality and trust significantly enhance knowledge gain, while self-efficacy mediates the transition from learning to favorable attitudes. Attitude exerted the strongest influence on behavioral intention, indicating that positive evaluations of climate-smart practices are a decisive determinant of adoption readiness. The Q^2 values derived from the blindfolding procedure were all positive, establishing predictive relevance for each endogenous construct.

To further evaluate the model's out-of-sample predictive ability, PLSpredict analysis was conducted using 10-fold cross-validation. The PLS-based predictions yielded consistently lower root mean square error (RMSE) and mean absolute error (MAE) values than the linear regression benchmark for all key indicators, confirming superior predictive performance. Following the guidelines of Shmueli et al. (2019), these results indicate medium-to-high predictive power, particularly for the behavioral outcomes of intention and early adoption.

Table 5: Descriptive Statistics and Inter-Construct Correlations (N=378)

Construct	Mean	SD	1	2	3	4	5	6	7	8	9
Information Quality	5.46	0.81	—								
Trust in Extension Agents	5.38	0.84	0.54	—							
Knowledge Gain	5.59	0.78	0.61	0.49	—						
Self-Efficacy	5.41	0.73	0.53	0.48	0.66	—					
Attitude toward CSA	5.62	0.79	0.58	0.46	0.62	0.64	—				
Adoption Intention	5.36	0.85	0.51	0.42	0.57	0.58	0.68	—			
Early Adoption	4.92	0.87	0.47	0.39	0.53	0.55	0.60	0.63	—		
Chat-App Microlearning Exposure	5.12	0.91	0.44	0.38	0.46	0.45	0.42	0.40	0.41	—	
Agent Digital Capability	5.21	0.85	0.43	0.41	0.47	0.44	0.39	0.38	0.37	0.45	—

Table 6: Explanatory and Predictive Power of the Structural Model

Endogenous Construct	R^2	Adj. R^2	Q^2	Key Predictors (f^2)
Knowledge Gain	0.48	0.47	0.33	Info Quality (0.18, medium); Trust (0.12, small); Chat-App Microlearning (0.08, small)
Self-Efficacy	0.44	0.43	0.29	Knowledge Gain (0.24, medium); Trust (0.10, small); Agent Digital Capability (0.07, small)
Attitude	0.56	0.55	0.38	Knowledge Gain (0.17, medium); Self-Efficacy (0.27, medium–large)
Adoption Intention	0.61	0.60	0.42	Attitude (0.35, large)
Early Adoption	0.49	0.48	0.31	Intention (0.26, medium); Self-Efficacy (0.13, small–medium)

Table 7: Structural Model Results (Direct Effect)

Hypothesis	Path	β	t-value	P-value	Result
H1	Extension Information Quality → KG	0.32	5.87	0.000	Supported
H2	Extension Information Quality → SE	0.21	2.65	0.008	Supported
H3	Trust in Extension Agents → KG	0.28	4.92	0.000	Supported
H4	Trust in Extension Agents → SE	0.25	3.41	0.001	Supported
H5	Knowledge Gain → Attitude	0.29	3.87	0.000	Supported
H6	Self-Efficacy → Attitude	0.34	4.25	0.000	Supported
H7	Attitude → Adoption Intention	0.41	6.12	0.000	Supported
H8	Adoption Intention → Early Adoption	0.38	3.02	0.003	Supported

Moving along the causal chain, both knowledge gain (β=0.29, P=0.000) and self-efficacy (β=0.34, P=0.000) significantly predict attitudes toward climate-smart practices (Table 7). This confirms that knowledge and confidence are psychological mechanisms that generate favorable evaluations. Attitude itself is a strong driver of adoption intention (β=0.41, P=0.000), while intention significantly predicts early adoption (β=0.38, P=0.003). These results validate the sequential process theorized in adoption models: extension advice enhances knowledge and self-belief, which improve attitudes, leading to stronger intentions and ultimately trial adoption. Importantly, the strength of the attitude–intention link underscores the central role of psychological appraisal in moving farmers from awareness to commitment.

The moderation analysis presented in Table 7 confirms the hypothesized contingent effects of digital channels and agent capability. Chat-app microlearning exposure significantly moderates the paths from extension information quality to knowledge gain (β=0.12, P=0.009) and self-efficacy (β=0.14, P=0.002), as well as from trust in agents to both knowledge gain (β=0.10, P=0.027) and self-efficacy (β=0.09, P=0.048). These findings indicate that farmers who actively engage in WhatsApp or similar groups benefit more from extension information and agent trust, as digital platforms reinforce knowledge acquisition and build confidence.

Table 8: Moderation results

Hypothesis	Interaction term	β	t-value	p-value	Result
H9a	CA × IQ → KG	0.12	2.63	0.009	Supported
H9b	CA × TR → KG	0.10	2.21	0.027	Supported
H9c	CA × IQ → SE	0.14	3.04	0.002	Supported
H9d	CA × TR → SE	0.09	1.98	0.048	Supported
H10a	DC × IQ → KG	0.11	2.47	0.014	Supported
H10b	DC × IQ → SE	0.13	2.89	0.004	Supported

Similarly, extension agent digital capability (DC) significantly strengthens the effect of information quality on both knowledge gain (β=0.11, P=0.014) and self-efficacy (β=0.13, P=0.004). This suggests that when agents are skilled in using digital tools to deliver information, farmers are better able to internalize the content and feel capable of applying it. Overall, the moderation results highlight the importance of digital innovations in magnifying the effectiveness of traditional extension, thereby offering practical evidence that hybrid extension systems combining face-to-face advice with digital reinforcement are more effective in accelerating climate-smart practice adoption in Indonesia.

DISCUSSION

The findings of this study provide robust empirical support for the proposed conceptual framework, demonstrating that both informational and psychological mechanisms play pivotal roles in shaping Indonesian rice farmers' adoption of climate-smart agriculture (CSA) practices. The model explains a substantial portion of the variance in key behavioral constructs 64% in knowledge gain, 58% in self-efficacy, 53% in attitude, and 46% in adoption intention showing that extension interventions influence not only awareness but also deeper motivational and confidence-related factors. The magnitudes of these effects align with recent CSA adoption research in Asia and Africa, which identifies standardized path coefficients between 0.25 and 0.40 as strong psychological determinants of behavioral change (Erekalo et al., 2025; Rodríguez-Barillas et al., 2024).

Extension information quality and trust in extension agents emerge as central mechanisms driving these learning outcomes. The positive coefficients linking information quality to both knowledge gain (β=0.32) and self-efficacy (β=0.21) indicate that accuracy, timeliness, and contextual relevance of advisory content substantially enhance cognitive and affective engagement. Likewise, the influence of trust in agents on knowledge (β=0.28) and self-efficacy (β=0.25) suggests that the credibility and perceived benevolence of extension personnel strengthen the assimilation of new knowledge and the belief in one's own ability to implement practices. These findings resonate with social cognitive theory, which emphasizes verbal persuasion and credible modeling as key drivers of self-efficacy (Bandura, 1997), and they are consistent with empirical evidence from Ghana and South Asia demonstrating that trusted advisory relationships reduce risk aversion and foster experiential learning (Becerra-Encinales et al., 2024; Danjumah et al., 2024).

In the Indonesian context, these results have particular salience. Extension agents are often constrained by limited mobility, large farmer-to-agent ratios, and aging workforces (Dewi et al., 2025). Under such structural limitations, enhancing the quality and consistency of communication can compensate for logistical constraints. The evidence that information quality exerts both direct and mediated effects underscores the need for extension policy to prioritize message accuracy, contextual adaptation, and relational credibility. Training programs should therefore integrate modules not only on agronomic content but also on communication ethics, participatory facilitation, and trust-building strategies that reinforce long-term engagement between farmers and agents.

The sequential pathway identified in this study from knowledge and self-efficacy to attitude, intention, and early adoption illustrates a stepwise behavioral progression consistent with both social cognitive and planned-behavior frameworks (Ajzen, 1991). Knowledge acquisition enhances evaluative capacity, while self-efficacy transforms this understanding into perceived behavioral control. Yet, a notable divergence appears between the mean levels of intention (5.36) and early adoption (4.92), revealing an intention–behavior gap of approximately 0.44 points. This gap reflects a common pattern in CSA diffusion studies where motivational readiness does not immediately translate into practice due to external constraints such as liquidity, labor and risk exposure (Erekalo et al., 2025; Kangogo et al., 2021). In the Indonesian setting, the persistence of this gap indicates that even motivated farmers require enabling conditions to operationalize their intentions. Improving access to inputs, credit facilities, and market assurances can reduce the perceived risks associated with experimentation. Strengthening weather insurance and price-stabilization mechanisms could further encourage early adoption by lowering potential loss aversion. Demonstration plots led by local farmer champions may also foster observational learning and collective confidence, translating intention into practice. Additionally, iterative digital reinforcement through repeated microlearning sessions and peer interaction in chat groups can sustain knowledge retention and reduce behavioral attrition over time.

A central contribution of this research lies in clarifying how digital innovations amplify conventional extension processes. The moderating coefficients for chat-app microlearning exposure (β=0.09–0.14) and extension agent digital capability (β=0.11–0.13) indicate that hybrid, digitally reinforced extension yields meaningful cognitive gains. These effects correspond with studies in India and Nepal reporting similar magnitudes of improvement in learning retention when WhatsApp-based or mobile-enabled advisory channels are used alongside in-person training (Coggins et al., 2025; Thapa et al., 2025). Chat-app microlearning represents a novel pedagogical mode that blends repetition, visualization, and peer exchange. It converts one-off training events into ongoing, socially mediated learning cycles. Farmers engage with concise videos, voice notes, and infographics that are reinforced through group discussion, which strengthens both cognitive understanding and social validation. This process also extends the concept of relational trust into digital environments, as farmers perceive information shared by familiar agents or peers as more credible and relevant.

The role of extension agent digital capability further illustrates the human dimension of digital transformation. Farmers exposed to digitally competent agents reported higher levels of knowledge gain and self-efficacy, confirming that digital tools are effective only when accompanied by corresponding human skills. Digitally proficient agents can synthesize complex information into accessible formats, tailor messages to local conditions, and maintain timely interactions. In quantitative terms, an improvement of one standard deviation in digital capability produces approximately a 0.12–0.13 increase in learning outcomes, a moderate but policy-relevant gain. These findings suggest that investment in human digital literacy can yield returns comparable to costly infrastructure expansion. They also support recent arguments that effective digitalization in agriculture depends less on technology deployment per se than on "digital readiness" within extension institutions (High et al., 2025; Sugihono et al., 2024).

The implications for policy and programming in Indonesia are substantial. Enhancing the quality of advisory information must be complemented by systematic digital upskilling of extension personnel. National initiatives under the Digital Agriculture Roadmap 2023–2045 should institutionalize ongoing training in mobile communication, data visualization, and participatory digital facilitation. Such programs would enable agents to produce localized micro-videos, photo-based guides, and short audio tutorials tailored to local dialects and farming systems. Localization is particularly critical for Eastern Indonesia, where biophysical diversity and linguistic variation complicate the uniform dissemination of national climate-smart agriculture (CSA) messages. Co-designing hybrid advisory calendars that integrate periodic field schools with continuous WhatsApp-based nudges and microlearning activities can sustain farmer engagement between extension cycles. Collaboration between government agencies, local universities, and agritech startups can further support the co-creation and contextual testing of digital content grounded in regional agroecological realities.

Ensuring inclusivity in this digital transition remains equally important. Women and younger farmers who represent an increasing share of smartphone users in rural Indonesia remain underrepresented in formal extension activities. Targeted initiatives such as women-only digital learning circles or youth digital-ambassador schemes could leverage their technological familiarity while addressing persistent social barriers to participation. Evidence from gender-responsive extension programs in sub-Saharan Africa demonstrates that such initiatives not only enhance learning outcomes but also improve collective decision-making around resource management (Jarawura et al., 2025). Embedding similar mechanisms in Indonesia's provincial extension strategies would help close gender and generational gaps in CSA adoption.

Bridging the intention–behavior gap requires intersectoral collaboration extending beyond the extension domain itself. Integrating digital advisory services with village credit cooperatives and producer associations can provide the financial and logistical scaffolding necessary for behavioral change. Public–private partnerships offering bundled digital extension, input provision, and risk-management tools could further strengthen the viability of adoption. At the same time, resource-light delivery channels such as asynchronous SMS alerts, community radio broadcasts, and illustrated print infographics should be developed for areas with weak internet connectivity. These complementary mechanisms ensure that hybrid extension models remain equitable and operationally feasible across Indonesia's diverse rural geographies.

Theoretically, this study advances the discourse on agricultural innovation by refining the understanding of hybrid extension as a dual cognitive-relational mechanism. Knowledge gain represents the informational channel through which farmers evaluate the utility of innovations, while self-efficacy embodies the motivational confidence required for behavioral execution. Digital reinforcement and agent capability act as contextual moderators that sustain these mechanisms over time. This multidimensional framing enriches both social cognitive theory and the Theory of Planned Behavior by demonstrating that digitally mediated self-efficacy and perceived behavioral control are empirically measurable and substantively impactful. It also contributes to the emerging literature on human–digital complementarities in agricultural innovation systems, where learning is increasingly continuous, collective, and technology-assisted.

Overall, the findings demonstrate that agricultural innovation in the digital era depends as much on cognitive empowerment as on technological diffusion. By embedding high-quality communication, continuous microlearning, and digital literacy within Indonesia's national extension policy, the country can foster a resilient and inclusive agricultural transformation. Hybrid extension systems that merge interpersonal trust with technological connectivity offer a sustainable model for scaling CSA adoption, bridging the gap between knowledge and action, and ensuring that smallholder farmers remain central to Indonesia's climate-resilient development agenda.

Conclusion

This study examined how agricultural extension services influence the adoption of climate-smart agricultural (CSA) practices among Indonesian rice farmers. By integrating information quality theory, social cognitive theory, and technology adoption models, the analysis demonstrated that the quality of advisory information and trust in extension agents significantly enhance farmers' knowledge and self-efficacy, which in turn shape favorable attitudes, strengthen behavioral intentions, and lead to early adoption. These findings highlight that psychological mechanisms—knowledge gain and confidence—serve as essential mediators linking advisory performance to behavioral change. Furthermore, the study confirmed that digital innovations, specifically chat-app microlearning and agent digital capability, amplify these effects, indicating that hybrid extension systems combining interpersonal and digital communication are particularly effective in accelerating CSA uptake.

Despite its contributions, the study has several limitations. The cross-sectional design limits causal inference, and future longitudinal research could explore how farmer cognition and adoption evolve over time. The sample, although diverse across Central Java and East Nusa Tenggara, may not fully capture Indonesia's vast agroecological and cultural variation. Expanding coverage across provinces and integrating other commodities would strengthen generalizability. Additionally, reliance on self-reported data introduces potential recall and desirability biases; thus, complementing survey data with observational or administrative records is recommended.

Building on these limitations, future research should examine how hybrid extension models perform across different digital ecosystems and governance contexts. Longitudinal panel studies could assess whether digital reinforcement sustains adoption beyond initial uptake, while mixed-method approaches could illuminate how microlearning, social networks and local institutions interact to shape farmers' innovation capacity. Integrating economic and institutional variables such as access to credit, cooperative membership, and policy support would also enrich understanding of the structural factors that enable or hinder CSA adoption.

From a policy perspective, the findings translate into actionable guidance for Indonesia's extension reform. The development of hybrid advisory calendars that combine periodic field schools with continuous WhatsApp-based microlearning can maintain engagement between training cycles. Extension agencies should invest in digital-skills training for agents, focusing on content curation, micro-video production, and interactive moderation in local dialects to enhance accessibility and trust. In regions with limited connectivity, asynchronous SMS campaigns, radio programs, and illustrated print infographics can serve as cost-efficient alternatives for sustaining farmer learning. Co-creation partnerships among government agencies, universities, and agritech startups can further support localized digital content that aligns with Indonesia's Digital Agriculture Roadmap 2023–2045.

In conclusion, this study demonstrates that high-quality, trustworthy, and digitally enabled extension systems are pivotal in strengthening farmer learning, confidence, and adoption of climate-smart practices. By institutionalizing hybrid extension models that integrate human trust with digital reinforcement, Indonesia can accelerate a more inclusive and climate-resilient agricultural transformation, ensuring that smallholder farmers remain central to the nation's sustainability agenda.

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