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Extension Support and Peer Influence on Climate-Smart Agriculture Adoption among Indonesian Rice Farmers

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HIGHLIGHTS

- Extension support strengthens farmers' behavioral intention and perceived ease of using climate-smart agriculture.
- Behavioral intention is the strongest direct predictor of realized CSA adoption among Indonesian smallholder rice farmers.
- Peer influence primarily improves perceived ease of use, highlighting the importance of farmer-to-farmer learning in CSA diffusion.

ARTICLE INFO

Keywords: Agricultural extension, Behavioural intention, Climate-smart agriculture, Peer influence, Technology acceptance model.

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ABSTRACT

Extension support and peer learning are widely promoted to accelerate climate-smart agriculture (CSA), but their relationships with farmers' cognitive evaluations and realized adoption remain insufficiently understood. This study examined CSA adoption among Indonesian smallholder rice farmers using a TAM-informed exploratory framework. A cross-sectional survey during 2025 involved 342 farmers in Sukra District, West Java, and Praya District, West Nusa Tenggara. Data were analyzed using partial least squares structural equation modelling. Extension support was positively associated with behavioural intention and perceived ease of use, while peer influence strongly predicted perceived ease of use but not behavioural intention. Farmer characteristics were associated with perceived ease of use but not behavioural intention. Behavioural intention was the strongest direct predictor of CSA adoption, followed by attitude toward CSA, whereas perceived ease of use had no significant direct relationship with adoption. The model explained 31.5% of the variance in adoption and demonstrated positive predictive relevance, although its out-of-sample predictive accuracy was limited. These findings indicate that extension should combine participatory demonstrations with farmer-to-farmer learning to strengthen operational confidence and intention to adopt CSA.

INTRODUCTION

Climate variability increasingly threatens rice-based farming, especially smallholders dependent on seasonal stability and limited production assets. Droughts, floods, and irregular rainfall disrupt planting, reduce yields, and threaten household income, compelling farmers in developing countries to adopt resilient yet productive practices (Acevedo et al., 2020; Hansen et al., 2018; Shilomboleni et al., 2024). These combined pressures make adaptation a production, livelihood, and environmental imperative for rice systems increasingly exposed to climatic shocks. Climate-Smart Agriculture (CSA) responds by integrating productivity, adaptation, and sustainable resource management (Islam et al., 2022; Mpala & Simatele, 2024; Vatsa et al., 2023; Zheng et al., 2024), while seeking

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to increase farm income, strengthen livelihood and ecosystem resilience, and reduce agricultural greenhouse gas emissions (Ma & Rahut, 2024).

Agricultural extension facilitates CSA diffusion by transferring knowledge, demonstrating applications, and reducing uncertainty, although its effects on adoption remain mixed (Rezaei-Moghaddam & Salehi, 2010; Lipper et al., 2017; Aggarwal et al., 2018: Shitu et al., 2018). In Karawang and Subang, government extension did not affect farmers' resilience capacity in one survey (Azhari et al., 2025a), whereas a larger survey identified extension implementation as a strong predictor of resilience and farm sustainability (Azhari et al., 2025b). This divergence may reflect extension capacity: Indonesian services remain production-oriented, while needs assessment, participatory facilitation, and business planning receive limited attention (Amanah et al., 2026). Peer learning also informs adoption through observation and farmer-group discussion, consistent with Social Learning Theory (Bandura, 1977). Explaining their joint influence therefore requires examining how farmers interpret information and evaluate technologies.

The Technology Acceptance Model (TAM), grounded in the Theory of Reasoned Action, explains adoption through cognitive evaluation and behavioral intention (Ajzen & Fishbein, 1980; Davis, 1989). Perceived usefulness and perceived ease of use are central determinants of attitude, intention, and technology use (Davis, 1989; Venkatesh et al., 2003; Venkatesh & Davis, 2000). In agriculture, experience, training, and social interaction shape these evaluations; extension and peer learning may therefore strengthen operational confidence and intention rather than constitute adoption itself (Ejigu & Yeshitela, 2024; Genius et al., 2014; Gemtou et al., 2024).

This study uses a TAM-informed exploratory framework for realized CSA adoption, positioning extension support, peer influence, and selected farmer characteristics as antecedents of perceived ease of use and behavioral intention. Perceived usefulness was excluded because no independent item validly measured it. The noncanonical Behavioral Intention → Attitude path is interpreted only as an exploratory cross-sectional association, not a causal sequence (Davis et al., 1989; Venkatesh & Bala, 2008; Ajzen & Schmidt, 2020).

Empirical models integrating extension, peer influence, cognitive evaluation, intention, and realized CSA adoption remain limited, particularly in rice-based systems (Mohr & Kühl, 2021; Rezaei-Moghaddam & Salehi, 2010). Smallholder studies more often apply the theory of planned behavior (Atta-Aidoo et al., 2022), while food-security technology reviews examine barriers without a cognitive model (Weisenfeld & Wetterberg, 2015). Using two Indonesian rice regions, this study tests relationships between behavioral intention, ease of use, attitude, and CSA adoption; examines extension, peer, and farmer-characteristic relationships with cognition; and evaluates out-of-sample predictive performance.

METHODOLOGY

Fieldwork was conducted during August–September 2025 in Sukra District, Indramayu Regency, West Java, and Praya District, Central Lombok Regency, West Nusa Tenggara. A cross-sectional survey applied a TAM-informed exploratory framework incorporating extension support, peer influence, and selected farmer characteristics as antecedents of farmers' cognitive evaluations and realized CSA adoption.

The population comprised 2,400 active rice farmers registered in formal farmer groups, which facilitate extension, information exchange, and learning. Because registration does not necessarily indicate active participation (Helmi et al., 2019), this sampling-frame limitation was considered when interpreting generalizability. Using Slovin's formula with a 5% margin of error (Slovin, 1960), 342 respondents were equally allocated between locations (171 each) and selected through proportional stratified random sampling at farmer-group level.

Trained enumerators conducted face-to-face interviews. The pilot-tested questionnaire adapted technology-acceptance and agricultural-adoption measures (Davis, 1989; Venkatesh & Bala, 2008; Zarei et al., 2022). Perceptual items used five-point Likert scales. Perceived ease of use and peer influence were reflective; extension support, selected farmer characteristics, and CSA adoption were formative. Behavioral intention and attitude were single-item constructs; the latter captured perceived benefits relative to previous practices. Their reliability and convergent validity could not be assessed (Diamantopoulos et al., 2012). Perceived usefulness was excluded because no item validly measured it. Adoption captured the number and duration of implemented CSA practices.

Data were processed using IBM SPSS Statistics 27.0 for descriptive analysis and SmartPLS 4.1.1.2 for model estimation and prediction. PLS-SEM was selected to estimate predictive models containing reflective and formative constructs (Hair et al., 2022; Sarstedt et al., 2022). Reflective measurement was evaluated using outer loadings, Cronbach's alpha, composite reliability, average variance extracted, and the heterotrait–monotrait ratio (Henseler et al., 2015). Formative measurement was assessed using outer weights, outer loadings, and variance inflation factors below 5. Structural assessment examined inner collinearity, path coefficients, R^2, and f^2 based on Cohen's (1988) benchmarks. Statistical significance was evaluated using 5,000 bootstrap subsamples and bias-corrected and accelerated confidence intervals. Predictive performance was assessed using blindfolding Q^2, ten-fold PLSpredict with ten repetitions, linear-model benchmarks (Shmueli et al., 2019), and SRMR, consistent with Indonesian rice research (Azhari et al., 2025b).

RESULTS

Assessment of the reflective measurement model

Perceived Ease of Use and Peer Farmer Influence were evaluated as reflective constructs. The three indicators of Perceived Ease of Use showed strong outer loadings, ranging from 0.933 to 0.953. The two indicators of Peer Farmer Influence had loadings of 0.660 and 0.954.

Composite reliability exceeded 0.70 for both reflective constructs, and their average variance extracted exceeded 0.50, supporting internal consistency and convergent validity. Cronbach's alpha for Peer Farmer Influence was 0.577; however, composite reliability reached 0.800. Given that the construct contained only two indicators, composite reliability was used as the primary internal-consistency criterion.

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Table 1. Indicator loadings in the CSA adoption model

Variable	Indicator	Outer loading
Agricultural Extension Support	Extension Module	0.759
	Frequency of Extension Visits	0.579
	Extension Worker Influence	0.707
	Intensity of Adoption Encouragement	0.831
Attitude toward CSA	Relative Advantage	1.000
CSA Adoption Level	Number of CSA Types Implemented	0.880
	Duration of CSA Use	0.570
Selected Farmer Characteristics	Activeness in Farmer Groups	0.902
	Farmer Education	0.585
Behavioral Intention	Intention to Adopt CSA	1.000
Perceived Ease of Use	Ease of Implementation	0.939
	Ease of Observation	0.953
	Ease of Testing	0.933
Peer Farmer Influence	Farmer Colleagues	0.954
	Farmer Figure	0.660

Source: Processed field data, 2025
Note: Loadings for formative indicators are supplementary; formative assessment is based primarily on outer weights and indicator collinearity.

Behavioral Intention and Attitude toward CSA were each measured using a single indicator. The attitude item operationalized an overall evaluation of CSA benefits relative to previous practices. Internal consistency and convergent validity could therefore not be assessed for either construct. Agricultural Extension Support, Selected Farmer Characteristics, and CSA Adoption Level were evaluated separately as formative constructs and were excluded from reflective reliability and validity assessment.

Discriminant validity between Perceived Ease of Use and Peer Farmer Influence was supported by an HTMT ratio of 0.550, with a 97.5% bootstrap upper bound of 0.657, below the threshold of 0.85 recommended by Henseler et al. (2015). HTMT was not assessed for pairs involving single-item or formative constructs.

Assessment of the formative measurement model

Agricultural Extension Support, Selected Farmer Characteristics, and CSA Adoption Level were assessed as formative constructs. All indicator variance inflation factors ranged from 1.013 to 2.045, remaining below the threshold of 5 and indicating no critical collinearity. All outer weights were positive and statistically significant at $p < 0.001$. Within Agricultural Extension Support, Intensity of Adoption Encouragement had the largest weight ($w = 0.465$), followed by Frequency of Extension Visits ($w = 0.354$), Extension Module ($w = 0.319$), and Extension Worker Influence ($w = 0.235$). Farmer-group activeness contributed more strongly to Selected Farmer Characteristics than formal education ($w = 0.824$ and 0.439, respectively). For CSA Adoption Level, the number of implemented practices had a larger weight than duration of use ($w = 0.827$ and 0.477, respectively). These results support indicator relevance and the absence of critical collinearity (Hair et al., 2022). Convergent validity through redundancy analysis could not be assessed because the instrument did not include independent global criteria for the formative constructs.

Structural model results

All inner VIF values were below 3.0, indicating that lateral collinearity did not materially affect the structural estimates. The model explained 44.6% of the variance in Behavioral Intention, 28.6% in Perceived Ease of Use, 18.9% in Attitude toward CSA, and 31.5% in CSA Adoption Level.

Behavioral Intention was the strongest predictor of CSA adoption ($\beta = 0.524$, $p < 0.001$), followed by Attitude toward CSA ($\beta = 0.186$, $p = 0.001$). Perceived Ease of Use was not significantly related to adoption ($\beta = -0.057$, $p = 0.457$), but it was strongly

Table 2. Measurement model evaluation: Cronbach's alpha, composite reliability, and AVE

Construct	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Perceived Ease of Use	0.936	0.959	0.887
Peer Farmer Influence	0.577	0.800	0.673

Source: Processed field data, 2025

Table 3. Heterotrait–monotrait (HTMT) ratios for the reflective constructs

Construct pair	HTMT	97.5% bootstrap upper bound	Below 0.85 threshold
Perceived Ease of Use – Peer Farmer Influence	0.550	0.657	Yes

Source: Processed field data, 2025

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Table 4. Formative measurement model: indicator collinearity, outer weights, and outer loadings

Construct	Indicator	VIF	Outer weight	t	p	Outer loading
Agricultural Extension Support	Extension Module	2.045	0.319	7.82	<0.001	0.759
	Frequency of Extension Visits	1.301	0.354	6.48	<0.001	0.579
	Extension Worker Influence	1.607	0.235	5.68	<0.001	0.707
	Intensity of Adoption Encouragement	1.788	0.465	11.61	<0.001	0.831
Selected Farmer Characteristics	Activeness in Farmer Groups	1.032	0.824	12.50	<0.001	0.902
	Farmer Education	1.032	0.439	4.58	<0.001	0.585
CSA Adoption Level	Number of CSA Types Implemented	1.013	0.827	17.31	<0.001	0.880
	Duration of CSA Use	1.013	0.477	7.68	<0.001	0.570

Source: Processed field data, 2025

associated with Behavioral Intention ($\beta = 0.581$, $p < 0.001$) and Attitude ($\beta = 0.458$, $p < 0.001$).

Extension support was positively related to Behavioral Intention ($\beta = 0.145$, $p = 0.006$) and Perceived Ease of Use ($\beta = 0.146$, $p = 0.004$). Peer influence was positively associated with Perceived Ease of Use ($\beta = 0.348$, $p < 0.001$) but not Behavioral Intention ($\beta = -0.023$, $p = 0.716$). Selected Farmer Characteristics were related to Perceived Ease of Use ($\beta = 0.172$, $p = 0.001$) but not Behavioral Intention ($\beta = 0.059$, $p = 0.157$). Behavioral Intention was not significantly associated with Attitude toward CSA ($\beta = -0.037$, $p = 0.638$).

An R^2 of 0.315 indicates that the model leaves approximately two-thirds of the variation in CSA adoption unexplained. Factors not included in the model—such as land tenure, credit access, irrigation reliability, input and output prices, and local group norms—may account for additional variation. The results therefore demonstrate meaningful cognitive and institutional associations but do not provide a complete explanation of CSA adoption.

Effect sizes and explanatory power

The largest structural effect was observed for Perceived Ease of Use on Behavioral Intention ($f^2 = 0.434$), followed by Behavioral Intention on CSA Adoption Level ($f^2 = 0.232$) and Perceived Ease of Use on Attitude toward CSA ($f^2 = 0.150$). Peer Farmer Influence had a small-to-medium effect on Perceived Ease of Use ($f^2 = 0.127$). Extension support had small effects on Behavioral Intention ($f^2 = 0.024$) and Perceived Ease of Use ($f^2 = 0.019$). The remaining effects were small or negligible. These results indicate that operational simplicity is most strongly associated with intention, while intention contributes most strongly to realized adoption.

Model fit and predictive assessment

Blindfolding produced positive Q^2 values for Behavioral Intention (0.424), CSA Adoption Level (0.241), Attitude toward CSA (0.179), and Perceived Ease of Use (0.152), indicating predictive relevance (Hair et al., 2022). PLSpredict also produced positive Q^2predict values ranging from 0.085 to 0.186. However, the PLS-SEM model generated slightly higher RMSE values than the linear-model benchmark for all available indicators, indicating low out-of-sample predictive power according to Shmueli et al. (2019). The SRMR values for the saturated and estimated models were 0.108 and 0.127, respectively, exceeding the conventional threshold of 0.08. Thus, the model demonstrates in-sample explanatory relevance but limited approximate fit and out-of-sample predictive accuracy.

DISCUSSION

Extension support was positively associated with both behavioral intention and perceived ease of use. This finding suggests that extension may contribute to CSA adoption by strengthening farmers' readiness to act and reducing uncertainty about implementation. Extension therefore functions as an enabling institutional mechanism rather than constituting adoption itself. This interpretation is consistent with diffusion-oriented perspectives

Table 5. Structural path estimates

Structural Path	Path Coefficient	T Statistics	P Value	Significance
Agricultural Extension Support → Behavioral Intention	0.145	2.738	0.006	Significant
Agricultural Extension Support → Perceived Ease of Use	0.146	2.872	0.004	Significant
Attitude toward CSA → CSA Adoption Level	0.186	3.285	0.001	Significant
Selected Farmer Characteristics → Behavioral Intention	0.059	1.415	0.157	Not Significant
Selected Farmer Characteristics → Perceived Ease of Use	0.172	3.596	0.001	Significant
Behavioral Intention → Attitude toward CSA	−0.037	0.470	0.638	Not Significant
Behavioral Intention → CSA Adoption Level	0.524	7.486	0.001	Significant
Perceived Ease of Use → Attitude toward CSA	0.458	6.612	0.001	Significant
Perceived Ease of Use → CSA Adoption Level	−0.057	0.744	0.457	Not Significant
Perceived Ease of Use → Behavioral Intention	0.581	11.921	0.001	Significant
Peer Farmer Influence → Behavioral Intention	−0.023	0.363	0.716	Not Significant
Peer Farmer Influence → Perceived Ease of Use	0.348	7.611	0.001	Significant

Source: Processed field data, 2025

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Table 6. Inner variance inflation factors and effect sizes of structural paths

Structural path	Inner VIF	f²	Effect size (Cohen, 1988)
Agricultural Extension Support → Behavioral Intention	1.565	0.024	Small
Agricultural Extension Support → Perceived Ease of Use	1.535	0.019	Small
Attitude toward CSA → CSA Adoption Level	1.233	0.041	Small
Selected Farmer Characteristics → Behavioral Intention	1.345	0.005	Negligible
Selected Farmer Characteristics → Perceived Ease of Use	1.304	0.032	Small
Behavioral Intention → Attitude toward CSA	1.727	0.001	Negligible
Behavioral Intention → CSA Adoption Level	1.729	0.232	Medium
Perceived Ease of Use → Attitude toward CSA	1.727	0.150	Medium
Perceived Ease of Use → CSA Adoption Level	1.986	0.002	Negligible
Perceived Ease of Use → Behavioral Intention	1.400	0.434	Large
Peer Farmer Influence → Behavioral Intention	1.513	0.001	Negligible
Peer Farmer Influence → Perceived Ease of Use	1.343	0.127	Small–medium

Source: Processed field data, 2025

Table 7. Approximate model fit, predictive relevance (Q^2), and PLSpredict results

Endogenous construct / indicator	Q^2 (Blindfolding)	Q^2predict	RMSE (PLS-SEM)	RMSE (LM)	Difference (PLS–LM)
Behavioral Intention	0.424	0.152	0.664	0.603	0.061
Perceived Ease of Use	0.152	–	–	–	–
• Ease of Implementation	–	0.117	0.9	0.895	0.005
• Ease of Observation	–	0.186	0.894	0.892	0.002
• Ease of Testing	–	0.142	0.899	0.892	0.007
Attitude toward CSA	0.179	0.139	0.817	0.805	0.011
CSA Adoption Level	0.241	–	–	–	–
• Number of CSA Types Implemented	–	0.085	0.985	0.975	0.01
• Duration of CSA Use	–	n.a.	n.a.	n.a.	n.a.
SRMR (Saturated model)	0.108	–	–	–	–
SRMR (Estimated model)	0.127	–	–	–	–

Source: Processed field data, 2025

emphasizing the informational and facilitative roles of agricultural advisory services (Rezaei-Moghaddam & Salehi, 2010). Evidence from West Java similarly shows that extension effects depend on implementation and interaction with farmers' human and social capital (Azhari et al., 2025a).

Peer influence was strongly associated with perceived ease of use but not behavioral intention. Observing neighboring farmers and discussing CSA practices within farmer groups may help farmers understand how a practice is implemented, tested, and adjusted under local conditions. Such interaction may improve operational confidence without necessarily creating a commitment to adopt. This pattern is consistent with Social Learning Theory, which emphasizes learning through observation and interaction (Bandura, 1977; Gerba et al., 2015; Ding et al., 2022; Shitu et al., 2024), and with evidence that social interaction is particularly relevant to farmers' assessments of technological feasibility (Genius et al., 2014).

Behavioral intention was the strongest predictor of realized CSA adoption, while attitude had a smaller positive relationship with adoption. Perceived ease of use was not directly associated with adoption, although it was strongly related to both intention and attitude. These findings are broadly consistent with TAM: operational simplicity can strengthen readiness and favorable evaluation, but actual implementation requires a sufficiently strong commitment to act. For smallholders, that commitment may also depend on resource availability, expected returns, and exposure to production risk (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Evidence from smallholder systems in West Sumatra supports this interpretation: farmers there adopted diversified cropping and crop-livestock arrangements, practices widely framed as adaptation to production and climate risk, mainly to stabilise income and maintain cash flow while awaiting the main harvest, whereas environmental motives were reported by only a small share of respondents (Utami et al., 2020). Operational simplicity may therefore be necessary but not sufficient, because adoption ultimately depends on whether a practice is judged capable of securing household income.

The findings support extension strategies combining participatory demonstrations with farmer-to-farmer learning. Demonstration plots can make implementation procedures and outcomes observable, while peer interaction can provide context-specific knowledge about operational constraints. Extension workers therefore need competencies in needs assessment, participatory facilitation, and business planning, rather than relying primarily on production-oriented information delivery (Amanah et al., 2026). However, the modest explanatory and predictive performance indicates that cognitive and institutional factors should be complemented by economic and structural conditions in future models.

Several limitations should be recognized. The cross-sectional design supports associations rather than causal or temporal

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conclusions. The Behavioral Intention → Attitude path differs from the canonical TAM sequence and should be interpreted as exploratory. Perceived usefulness was not included because no independent item validly measured the construct. Behavioral intention and attitude were measured with single items, and the attitude item represented perceived benefits relative to previous practices; consequently, their internal consistency and convergent validity could not be assessed. Convergent validity of the formative constructs could not be examined through redundancy analysis because independent global criteria were unavailable. Adoption was self-reported, and perceptions may have been influenced by previous adoption experiences. The study covered only two rice-producing areas and used farmer-group registers as its sampling frame, which may under-represent farmers belonging to inactive groups (Helmi et al., 2019). The model also excluded land tenure, credit access, irrigation reliability, prices, and other structural constraints. These limitations restrict generalization and help explain the model's limited out-of-sample predictive accuracy.

CONCLUSION

Among 342 rice farmers in Sukra and Praya, extension support was positively associated with behavioral intention and perceived ease of using CSA, while peer influence was primarily associated with perceived ease of use. Behavioral intention was the strongest predictor of realized adoption, followed by attitude, whereas perceived ease of use had no significant direct relationship with adoption. These findings indicate that extension and peer learning contribute differently to CSA acceptance: extension strengthens readiness to adopt, while farmer-to-farmer interaction builds operational confidence. Extension programs should therefore combine participatory demonstrations, locally documented outcomes, and peer-learning activities. Nevertheless, the model's moderate explanatory capacity and limited out-of-sample predictive accuracy indicate that future studies should incorporate economic, institutional, and resource-related constraints and employ longitudinal designs to clarify the transition from intention to sustained CSA adoption.

DECLARATIONS

Ethics approval and informed consent: The study was approved by the Research Ethics Committee, Universitas Pendidikan Indonesia, under ethical approval No. 101/UN40.K/PT.01.01/2025. All participants provided informed consent before participating in the study.

Data availability statement: The datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request. The data are not publicly available because they contain information that could compromise participant confidentiality.

Software used: Data were analyzed using SmartPLS 4.1.1.2 (SmartPLS GmbH, Oststeinbek, Germany) for partial least squares structural equation modeling (PLS-SEM) and IBM SPSS Statistics version 27.0 (IBM Corp., Armonk, NY, USA) for descriptive statistical analysis.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors declare that during the preparation of this work, they thoroughly reviewed, revised, and edited the content as needed. The authors take full responsibility for the final content of this publication.

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APPENDIX

Table A1. Constructs, indicators, measurement items, and sources

Construct	Indicator	Measurement Item	Scale	Adapted From
Agricultural Extension Support	Extension Module	Number of CSA training topics received and completeness of technical extension materials.	5-point ordinal scale	Zarei et al. (2022); contextualized for Indonesian CSA extension
	Frequency of Extension Visits	Frequency of extension worker visits during each cropping season.	5-point frequency scale	Zarei et al. (2022)
	Extension Worker Influence	Extent to which extension workers influence farmers' decisions to adopt CSA technologies.	5-point Likert	Zarei et al. (2022)
	Intensity of Adoption Encouragement	Frequency with which extension workers directly encouraged CSA adoption during the past two years.	5-point frequency scale	Zarei et al. (2022)
Peer Farmer Influence	Farmer Colleagues	Number of farmer group members adopting CSA and frequency of CSA discussions during farmer group meetings.	5-point ordinal/ frequency scale	Zarei et al. (2022); Social Learning Theory
	Farmer Figure	Frequency of following recommendations from lead farmers and perceived influence of successful model farmers.	5-point Likert	Zarei et al. (2022)
Selected Farmer Characteristics	Activeness in Farmer Groups	Level of participation in farmer group activities.	5-point participation scale	Developed for this study
	Farmer Education	Highest level of formal education completed.	Ordinal categories	Developed for this study
Perceived Ease of Use	Ease of Implementation	CSA technologies are easy to implement.	5-point Likert (1 = Strongly disagree to 5 = Strongly agree)	Davis (1989); Venkatesh & Bala (2008)
	Ease of Observation	The results of CSA implementation are easy to observe.	5-point Likert	Davis (1989); Venkatesh & Bala (2008)
	Ease of Testing	CSA technologies are easy to trial before full adoption.	5-point Likert	Davis (1989); Venkatesh & Bala (2008)
Behavioral Intention	Intention to Adopt CSA	Likelihood of adopting CSA technologies in the next cropping season.	5-point Likert	Davis (1989); Venkatesh & Bala (2008)
Attitude toward CSA	Relative Advantage	CSA technologies provide greater benefits than previous farming practices.	5-point Likert	Davis (1989); Rogers (2003)
	Number of CSA Types	Total number of CSA technologies currently adopted.	Count/index	Adapted from Zarei et al. (2022)
CSA Adoption Level	Duration of CSA Use	Year in which the farmer first adopted CSA technologies.	Years of adoption	Adapted from Zarei et al. (2022)

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