# Perceived Usefulness and Perceived Ease of Use as Predictors of Attitude Toward IoT Adoption Among Rice Farmers

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***Abstract*—This study investigates key drivers influencing rice farmers' attitudes toward Internet of Things (IoT) adoption in Indonesia, using the Technology Acceptance Model (TAM) as an analytical lens. Specifically, it evaluates the predictive roles of Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), both of which are posited to shape users' Attitude Toward Usage (ATT). Survey data were obtained from 62 smallholder farmers in Bandung Regency and examined through Partial Least Squares Structural Equation Modeling (PLS-SEM). The study confirms that both PU and PEOU significantly contribute to the formation of favorable farmer attitudes, with the model showing high explanatory strength ($R^2$ = 0.723). PU captures the perceived benefit of IoT for improving productivity and efficiency, while PEOU reflects user-friendly design and ease of integration into existing agricultural routines. These findings extend TAM's validity in rural, low-tech farming contexts and offer actionable insights for technology developers, government agencies, and agricultural organizations seeking to foster digital transformation. By confirming the relevance of usability and perceived value, this study supports targeted design and communication strategies that align with farmers' expectations. It also lays the groundwork for broader ASEAN agricultural resilience efforts by emphasizing inclusive technology pathways. Future research may incorporate sociocultural dimensions and systemic barriers to expand the model's applicability in diverse farming environments.**

***Keywords*—*IoT; attitude towards IoT; Perceived Usefulness; Perceived Ease of Use; technology adoption***

## I. Introduction

The Internet of Things (IoT) holds considerable promise in transforming the agricultural sector by improving efficiency, productivity, and sustainability [1]. In the context of rice farming, IoT applications include monitoring environmental conditions, optimizing irrigation, and delivering real-time data to support informed decision-making [2]. Despite these advantages, IoT adoption among farmers remains limited, and gaining insight into the factors influencing their attitudes is essential for effective implementation [3], [4].

Attitude plays a central role in shaping an individual's intention and behavior toward adopting new technology. The Technology Acceptance Model (TAM), a commonly utilized framework in technology adoption research, identifies Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as key antecedents of attitude [5], [6]. PU denotes the perception that the utilization of a specific technology enhances task efficiency, whereas PEOU reflects the notion that the technology is easy to operate.

For rice farmers, cultivating a positive attitude toward IoT adaption (ATT) is a critical step in encouraging experimentation and adoption [4], [7]. Accordingly, this research explores how PU and PEOU shape farmers' attitudes within the TAM framework, focusing on rice farmers in Bandung Regency, West Java, Indonesia [8].

TAM has been widely applied across diverse technological domains, consistently validating the predictive strength of PU and PEOU in shaping attitudes toward technology [9], [10], [11]. In agriculture specifically, several studies affirm the significance of these constructs in driving the adoption of technological innovations [12], [13].

Nonetheless, prior research also acknowledges that other variables—such as individual innovativeness, trust, and social norms—may influence farmers' attitudes [12], [14]. While recognizing the multifaceted nature of technology adoption, this study purposefully concentrates on the foundational constructs within TAM.

Despite the existing body of literature, a research gap persists in understanding how PU and PEOU specifically affect rice farmers' ATT. This study addresses this gap by drawing on empirical data from rice farmers in Bandung Regency.

Accordingly, the research centers on evaluating the impact of these two constructs in shaping farmer attitudes. The central questions are formalized into the following hypotheses:

- H9: How does Perceived Usefulness (PU) influence rice farmers' attitudes toward IoT adaption (ATT)?
- H11: How does Perceived Ease of Use (PEOU) influence rice farmers' attitudes toward IoT adaption (ATT)?

This study is principally designed to investigate how PU and PEOU shape farmers' ATT. The study contributes theoretically by extending the application of TAM to agricultural IoT contexts, and practically by offering insights for stakeholders—government agencies, technology developers, and farming organizations—on how to cultivate positive farmer perceptions through targeted interventions that highlight both usefulness and usability.

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## II. Literature Review

### A. Internet of Things (IoT) in Agriculture

IoT is increasingly recognized as a pivotal innovation capable of reshaping multiple industries [15], [16], [17], [18], [19], [20], including agriculture [21], [22], [23]. IoT in agriculture entails deploying sensors, actuators, and other interconnected devices to gather and transmit information related to various aspects of farming operations, including environmental parameters, crop vitality, and soil characteristics. The resulting data can be processed to generate actionable knowledge for farmers, supporting more precise decision-making and enhancing agricultural efficiency.

The potential benefits of IoT in rice farming are substantial. For example, IoT sensors can monitor soil moisture levels and automate irrigation, reducing water waste and increasing crop yields [19], [21], [24], [25], [26], [27], [28], [29]. Drones integrated with IoT imaging systems can assess plant health and facilitate early detection of agricultural threats, allowing for timely intervention [30], [31], [32], [33], [34]. IoT can also assist in optimizing fertilizer use, minimizing environmental impact, and enhancing overall efficiency.

### B. Technology Acceptance Model (TAM)

TAM is among the predominant theoretical frameworks for understanding how individuals accept and adopt information technologies [35], [36], [37]. According to TAM, a person's attitude toward utilizing a technology is shaped by two central perceptions: Perceived Usefulness (PU), which represents the notion that the technology contributes to improved job performance [38], [39], and PEOU, which embodies the notion that the system requires minimal effort to operate [10].

TAM argues that PU and PEOU positively influence ATT [40], which subsequently shapes the behavioral tendency toward adopting the technology [41]. Within the scope of this research, TAM serves as a relevant framework for examining how rice farmers engage with and embrace IoT technology. The questionnaire employed in the present work assesses PU and PEOU using measurement scales derived from previously validated TAM instruments. Although TAM has been expanded with various external constructs in prior studies, the current analysis concentrates on the fundamental linkage between PU and PEOU as principal predictors of ATT.

### C. Perceived Usefulness and Attitude Towards IoT

PU is a significant predictor of ATT [10]. if they perceive improvements in task efficiency or outcome quality. [42]. In the context of rice farming, farmers may perceive IoT as useful if it can help them to increase crop yields, reduce input costs (e.g., water, fertilizer), save time and labor, and make better-informed decisions [43].

Prior research has demonstrated that PU significantly influences ATT of various agricultural technologies, such as farm information systems and precision agriculture technologies [44]. Therefore, this study hypothesizes (H9) that PU positively influences rice farmers' ATT.

### D. Perceived Ease of Use and Attitude Toward IoT

PEOU is also an important factor in shaping ATT [10]. Individuals tend to have a positive ATT if they perceive it as easy to learn, easy to use, and requiring minimal mental effort [45].

In the context of rice farming, farmers may perceive IoT as easy to use if the user interface is intuitive, the system is reliable and stable, training and support are readily available, and the technology is compatible with existing farming practices [46], [47].

Previous research has found that PEOU significantly affects ATT across different domains, including agriculture [14], [48]. Hence, this study hypothesizes (H11) that PEOU positively influences rice farmers' ATT.

### E. Attitude Towards IoT and Adoption Intention

ATT represents a person's general assessment of the IoT technology, reflecting their positive or negative feelings about it. A positive attitude toward technology is likely to lead to a stronger intention to adopt and use it [14], [49].

In this study, rice farmers' ATT refers to their feelings and evaluations regarding the use of IoT in their farming practices. The questionnaire used in this research measures farmers' ATT using items that assess their feelings about using IoT for collaborative farming [50], [51].

Prior research consistently demonstrates a robust association between attitude toward technology and adoption intention. Therefore, this study hypothesizes that rice farmers' positive attitude toward IoT enhances their behavioral intention toward adopting the technology.

### F. Conceptual Framework

Framework Representing TAM and Associated Determinants as presented in Fig. 1.

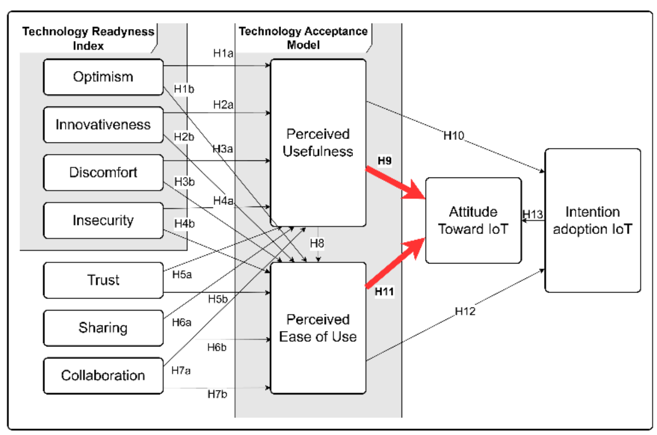


Fig. 1. Framework representing the technology acceptance model and influencing factors.

Fig. 1 illustrates the analytical model developed for this research. This model is based on the TAM, which posits that an individual's intention to embrace a technology is influenced by their ATT. That attitude, in turn, is principally guided by two core constructs: PU and PEOU. In this study, we specifically examine the relationships between PU, PEOU, ATT, and

Intention Adoption IoT. The framework also illustrates those other factors, such as Optimism, Innovativeness, Discomfort, Insecurity, Trust, Sharing, and Collaboration, can influence farmers' perceptions of PU and PEOU. While these factors are acknowledged, the analysis centers on the direct effects among PU (H9) and PEOU (H11) toward ATT, which constitute the fundamental constructs of the TAM framework.

## III. Methodology

### A. Research Design

This study employs a quantitative approach utilizing survey methodology -based method to examine the elements affecting rice farmers' ATT. A standardized questionnaire was applied to methodically gather information from farmers concerning their views and dispositions. The research process is systematically illustrated in Fig. 2, detailing the stages from conceptualization to data collection and analysis.

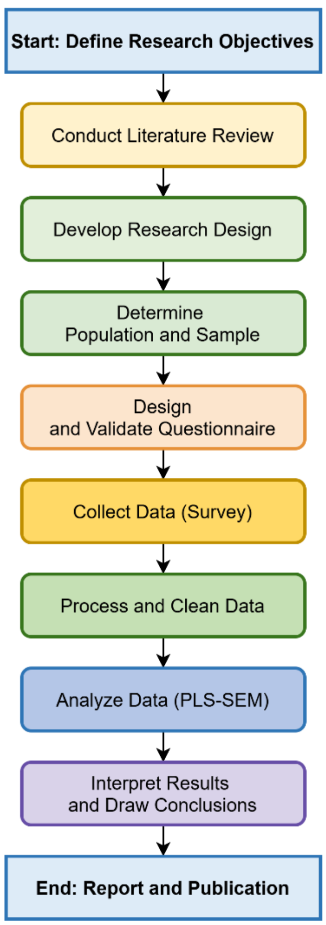


Fig. 2. Research process flowchart for IoT adoption study.

The survey method was chosen as it allows for statistical analysis of predefined variables—PU, PEOU, and ATT—and enables generalization of findings to a broader population. Given that IoT adoption in agriculture is still emerging, this approach provides empirical insights into farmers' acceptance of new technology.

### B. Population and Sample

*1) Target population:* The population under investigation comprises rice farmers from Bandung Regency, West Java, Indonesia.

*2) Sampling method:* This study employed both purposive and stratified sampling techniques to ensure targeted and representative respondent selection to ensure a representative and relevant dataset:

*a)* Purposive Sampling was employed to select farmers who had prior exposure to IoT technology in agricultural practices. This ensured that respondents had a sufficient understanding of IoT to provide meaningful insights into its usefulness and ease of use.

*b)* Stratified Sampling was applied based on farmers' land size, farming experience, and education level, ensuring balanced representation across different categories of respondents.

*3) Sample size determination:* A total of 62 rice farmers were selected as respondents. The sample size was determined based on statistical power analysis, ensuring that it provides sufficient data for meaningful inference while maintaining computational efficiency for PLS-SEM analysis. While this sample size is appropriate for PLS-SEM, it should be noted that generalizing the findings to a broader population of rice farmers may require caution, given the inherent contextual variations.

### C. Research Instrument

Primary empirical input was obtained through a standardized instrument, divided into two discrete components:

- Section 1: Demographic Information – Collected respondents' age, gender, education level, and farming experience to provide contextual insights.
- Section 2: Measurement of Study Variables – Included statements assessing PU, PEOU, and ATT, assessed through A 7-point Likert-type scale were adopted, with endpoints defined as 1 (strongly disagree) and 7 (strongly agree).

All survey indicators were derived from established scales validated in prior research on technology adoption. Respondents completed the questionnaire under the guidance of enumerators, who assisted in clarifying questions to ensure accurate responses.

### D. Data Collection Procedure

Data collection was conducted through direct questionnaire distribution, with enumerators supervising the process to facilitate respondent understanding. The data collection period was February 9th to February 12th, 2025.

Before survey administration, participants received details concerning the aims of the research, assurance of response privacy, and participants' entitlement to withdraw at any phase.

Informed consent was obtained from all respondents before proceeding with data collection. The data collection procedure and analytical approach are illustrated in Fig. 1, providing a step-by-step breakdown from administration to statistical processing.

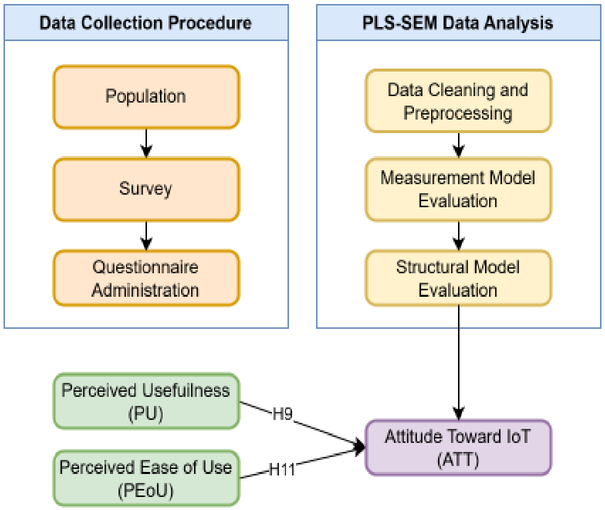


Fig. 1. Data collection and analysis framework.

This diagram illustrates the data collection procedure and analysis workflow for this study. It outlines the structured process from sampling selection to hypothesis testing, utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to map the causal pathways linking principal constructs.

The hypotheses tested in the analysis have been updated to match the conceptual framework outlined in the Literature Review and the structure of the Results Section. Specifically, H9 and H11.

Each stage of the analysis follows a systematic approach, starting with data cleaning and preprocessing, followed by measurement model evaluation, and concluding with structural model validation and hypothesis testing using Smart PLS 3 software.

### E. Data Analysis Methods

The collected data underwent analysis using both descriptive and inferential statistical techniques, as illustrated in Fig. 1. Demographic profiles of the respondents were outlined using descriptive statistical techniques respondents, including measures such as frequencies, percentages, means, and standard deviations. Furthermore, PLS-SEM was selected as the analytical technique to test the hypothesized paths between constructs, owing to its capacity to accommodate complex models and its applicability in contexts with modest sample sizes. Furthermore, its relaxed assumptions regarding data distribution made it a suitable choice for this study. All computations were carried out using SmartPLS 3. The detailed evaluation of the measurement and structural models, including criteria and results, will be presented in the "PLS-SEM Analysis" section under Results and Discussion.

## IV. Results and Discussion

The subsequent part delineates empirical outputs and interprets the observed influences on rice farmers' ATT. The results include the characteristics of the respondents, the assessment of instrument validity and reliability, along with the PLS-SEM results employed to examine the hypotheses concerning PU, PEOU, and ATT.

### A. Respondent Characteristics

The data on respondent characteristics are presented to provide an overview of the participants' backgrounds and the research context. This information is relevant for interpreting the analysis results related to ATT.

Table I presents the frequency distributions of respondents based on their demographic characteristics and technology usage. The following tables present the characteristics of the 62 respondents who participated in the survey conducted between February 9th and February 12th, 2025.

TABLE I. Demographic and Farming Characteristics of Respondents

| Respondent Characteristic | Categories | Frequency | Percentage |
|---|---|---|---|
| Age | 29 years or younger | 1 | 1.61% |
| | 30-39 years | 9 | 14.52% |
| | 40-49 years | 11 | 17.74% |
| | 50-59 years | 25 | 40.32% |
| | 60 years or older | 16 | 25.81% |
| Gender | Male | 46 | 74.19% |
| | Female | 16 | 25.81% |
| Rice Field Area | <0.5 hectares | 19 | 30.65% |
| | 0.5-1 hectare | 26 | 41.94% |
| | 1-2 hectares | 17 | 27.42% |
| Farming Experience | 1-5 years | 6 | 9.68% |
| | 6-10 years | 6 | 9.68% |
| | 11-15 years | 10 | 16.13% |
| | 16-20 years | 17 | 27.42% |
| | 21-25 years | 17 | 27.42% |
| | >25 years | 6 | 9.68% |
| Education Level | No formal education | 1 | 1.61% |
| | Elementary school | 43 | 69.35% |
| | Junior high school | 15 | 24.19% |
| | Senior high school | 3 | 4.84% |
| Technology Use in Farming | Never | 59 | 95.16% |
| | Rarely/Occasionally | 3 | 4.84% |

### B. Validity and Reliability Tests

Instrument validity was assessed to confirm that the measurement items appropriately capture the targeted constructs. In this study, the validity was tested through Pearson correlation analysis, which quantifies the strength and direction of the linear relationship between each statement item and the overall construct. A correlation coefficient above 0.3 indicates that the item is valid and meaningfully contributes to measuring the construct.

Table II presents the revised questionnaire items used to measure each construct—PU, PEOU, ATT, and Intention to Adopt IoT. Each item was adapted from validated TAM instruments and reworded to preserve academic neutrality and consistency.

TABLE II. VALIDITY TEST RESULTS OF IOT ADOPTION CONSTRUCTS

| Variable | Statement Item | Calculated r | Critical r | Validity |
|---|---|---|---|---|
| Perceived Usefulness (PU) | IoT technology is perceived to improve rice harvest outcomes. | 0.987 | 0.3 | Valid |
| | IoT enables discovery of efficient and modern agricultural practices. | 0.989 | 0.3 | Valid |
| | IoT enhances farm management capabilities. | 0.99 | 0.3 | Valid |
| | IoT contributes to faster task completion in rice fields. | 0.974 | 0.3 | Valid |
| Perceived Ease of Use (PEOU) | IoT is considered easy to operate in rice farming. | 0.828 | 0.3 | Valid |
| | IoT is perceived as easily integrable into farming routines. | 0.912 | 0.3 | Valid |
| | Functions of IoT in farming are easy to comprehend. | 0.907 | 0.3 | Valid |
| | IoT technology adapts well to individual farming needs. | 0.919 | 0.3 | Valid |
| Attitude Toward IoT adaption (ATT) | IoT facilitates collaborative farming to improve yields. | 0.947 | 0.3 | Valid |
| | Farmers are inclined to share experiences via IoT platforms. | 0.926 | 0.3 | Valid |
| | IoT is preferred over traditional coordination methods. | 0.96 | 0.3 | Valid |
| | Enthusiasm exists for using IoT to support agricultural cooperation. | 0.955 | 0.3 | Valid |
| Intention to Adopt IoT | Farmers plan to apply IoT in future rice farming. | 0.984 | 0.3 | Valid |
| | IoT is seen as instrumental for increasing productivity. | 0.984 | 0.3 | Valid |
| | Interest exists in exploring diverse IoT applications for farming. | 0.986 | 0.3 | Valid |
| | Farmers intend to recommend IoT if proven beneficial. | 0.979 | 0.3 | Valid |

Table II present the validity test results for four key variables: PU, PEOU, ATT, and Intention to Adopt IoT. Each statement item within these constructs was examined to verify its reliability in capturing respondent perceptions. The correlation coefficients for all items exceed the critical threshold of 0.3, confirming their validity as research indicators.

The validation results underscore the robustness of the instrument used in this study, ensuring that the measured variables accurately reflect respondents' perceptions and attitudes. This validation strengthens the subsequent analysis, enabling precise interpretation of IoT adoption tendencies within the agricultural sector.

Reliability assessment employed Cronbach's Alpha as a metric for internal consistency, adopting 0.6 as the minimum acceptable threshold.

Table III displays the outcomes of the reliability assessment, showing that all constructs exhibit acceptable internal consistency ($\alpha > 0.6$).

TABLE III. RELIABILITY TEST RESULTS

| Variable | Reliability Index | Critical Value | Result |
|---|---|---|---|
| Perceived Usefulness | 0.989 | 0.6 | Reliable |
| Perceived Ease of Use | 0.912 | 0.6 | Reliable |
| Attitude Toward IoT | 0.959 | 0.6 | Reliable |
| Intention Adoption IoT | 0.988 | 0.6 | Reliable |

### C. PLS-SEM Analysis

Multiple statistical procedures were applied to confirm the reliability and validity of the measurement tool.

*1) Convergent validity:* Convergent validity was assessed to determine whether indicators effectively measure their respective constructs. Factor loadings and Average Variance Extracted (AVE) were used to evaluate this, with thresholds suggesting validity are factor loadings > 0.6 and AVE > 0.5, indicating strong construct validity (Table IV).

TABLE IV. LOADING FACTOR AND AVE RESULTS

| Construct | Indicator | Factor Loading | Critical Value | AVE |
|---|---|---|---|---|
| Attitude Toward IoT | ATT1 | 0.951 | 0.6 | 0.897 |
| | ATT2 | 0.937 | 0.6 | |
| | ATT3 | 0.954 | 0.6 | |
| | ATT4 | 0.947 | 0.6 | |
| Perceived Ease of Use | PEOU1 | 0.852 | 0.6 | 0.793 |
| | PEOU2 | 0.89 | 0.6 | |
| | PEOU3 | 0.885 | 0.6 | |
| | PEOU4 | 0.934 | 0.6 | |
| Perceived Usefulness | PU1 | 0.987 | 0.6 | 0.97 |
| | PU2 | 0.99 | 0.6 | |
| | PU3 | 0.99 | 0.6 | |
| | PU4 | 0.974 | 0.6 | |

*2) Discriminant validity:* It serves to verify that no latent variable overlaps significantly with another, maintaining construct independence. The cross-loading test was performed to verify whether indicators correlate more strongly with their designated construct than with other constructs (Table V).

TABLE V. CROSS-LOADING RESULTS

| Attitude Toward IoT | Perceived Ease of Use | Perceived Usefulness | Result |
|---|---|---|---|
| ATT1 | 0.951 | 0.777 | 0.786 |
| ATT2 | 0.937 | 0.801 | 0.795 |
| ATT3 | 0.954 | 0.719 | 0.782 |
| ATT4 | 0.947 | 0.705 | 0.752 |
| PEOU1 | 0.785 | 0.852 | 0.698 |
| PEOU2 | 0.535 | 0.89 | 0.5 |
| PEOU3 | 0.50. 5 | 0.885 | 0.472 |
| PEOU4 | 0.687 | 0.934 | 0.651 |
| PU1 | 0.761 | 0.698 | 0.987 |
| PU2 | 0.76 | 0.5 | 0.99 |
| PU3 | 0.776 | 0.472 | 0.99 |
| PU4 | 0.826 | 0.651 | 0.974 |

*3) Reliability test:* The reliability coefficients derived from Cronbach's Alpha and Composite Reliability, where values above 0.7 are considered indicative of robust internal consistency (Table VI).

TABLE VI. RELIABILITY TEST RESULTS

| Latent Variable | Average Variance Extracted (AVE) | Critical Value | Criterion (AVE > 0.5) |
|---|---|---|---|
| Attitude Toward IoT | 0.897 | 0.5 | Valid |
| Perceived Ease of Use | 0.793 | 0.5 | Valid |
| Perceived Usefulness | 0.97 | 0.5 | Valid |

*4) Structural model evaluation:* Structural model evaluation was conducted to examine inter-construct linkages through multiple analytical indicators.

R-Square ($R^2$) quantifies how predictor variables explain fluctuations within the target construct (Table VII).

TABLE VII. R-SQUARE RESULTS

| Dependent Variable | R-Square | Strength of relationship |
|---|---|---|
| Attitude Toward IoT | 0.723 | Strong |

Effect Size (f-Square) measures the impact of the influence of predictor variables on the outcome variable (Table VIII).

TABLE VIII. F-SQUARE EFFECT SIZE

| Independent Variable | Attitude Toward IoT |
|---|---|
| Perceived Ease of Use | 0.337 |
| Perceived Usefulness | 0.732 |

Predictive Relevance ($Q^2$). Predictive relevance ($Q^2$) was tested to measure the predictive capacity of the model future outcomes (Table IX).

TABLE IX. $Q^2$ PREDICTIVE RELEVANCE RESULTS

| Dependent Variable | SSO | SSE | $Q^2$ Value |
|---|---|---|---|
| Attitude Toward IoT | 248 | 91.378 | 0.632 |

*5) Hypothesis testing:* Hypothesis testing was conducted to determine whether the proposed relationships between constructs reach statistical significance, indicating that bot PU and PEOU significantly influence ATT (Table X).

TABLE X. PATH COEFFICIENTS AND P-VALUES

| Hypothesis | Variable | Original sample (O) | T-statistics (\|O/STDEV\|) | P-values (5%) | Result |
|---|---|---|---|---|---|
| H9 | Perceived Usefulness -> Attitude Toward IoT | 0.564 | 4,613 | <0.001 | Supported |
| H11 | Perceived Ease of Use -> Attitude Toward IoT | 0.382 | 3,454 | 0.001 | Supported |

The results in Table X confirm that both hypotheses are statistically supported. For H9, the relationship between PU and ATT, the path coefficient is 0.564, accompanied by a T-statistic of 4.613 and a P-value below 0.001, indicating a statistically significant relationship. Since the T-statistic (4.613) surpasses the established benchmark of 1.96 and the P-value (<0.001) falls below the 0.05 significance level, the proposed hypothesis is confirmed by empirical evidence. This finding confirms that PU exerts a significant positive effect on rice farmers' ATT.

Similarly, H11 is supported by a path coefficient of 0.382, a T-statistic of 3.454, and a P-value of 0.001—each meeting the criteria for statistical significance ($T > 1.96$; $P < 0.05$). The data confirm that PEOU has a meaningful and beneficial influence on rice farmers' ATT. This confirms that PPEOU significantly and positively influences farmers' ATT. The results confirm that the relationships involving PU and PEOU are statistically supported antecedents of rice farmers' ATT, reinforcing the theoretical premises of TAM.

### D. Discussion

This study provides empirical evidence on the key factors influencing rice farmers' Attitude Toward Technology (ATT) within the agricultural domain. Consistent with the TAM and prior research, PU was found to significantly influence ATT. When farmers perceive IoT as a beneficial tool for enhancing productivity—such as improving crop yields, reducing operational costs, and increasing time efficiency—they are more inclined to adopt a positive stance.

Similarly, PEOU emerged as a key factor in shaping attitudes, reaffirming TAM's emphasis on usability. Farmers who regard IoT as intuitive and straightforward to use tend to demonstrate a higher propensity for adoption. This underscores the practical relevance of ergonomic system architecture, focused capacity-building initiatives, and readily available technical assistance.

While this study primarily concentrates on PU and PEOU, it is essential to recognize that additional variables—such as cultural context, social influence, and personal innovativeness—may also affect farmers' technology perceptions. Future research could extend the model to include these complementary dimensions.

Within the scope of this analysis, however, our focus remains on the central constructs grounded in TAM. The hypotheses tested (H9 and H11) confirm the significant impact of PU and PEOU as principal predictors of ATT, supporting the robustness of the conceptual framework.

## V. Conclusion

This study analyzed the factors influencing rice farmers' attitudes toward IoT adoption, emphasizing Perceived Usefulness (PU) and Perceived Ease of Use (PEOU).

### A. Key Findings

- PU significantly influences farmers' attitudes toward IoT adoption. Farmers who recognize IoT as beneficial for improving farming practices—such as enhancing crop yields and efficiency — have an increased propensity to form a positive attitude toward the technology.
- PEOU significantly impacts farmers' attitudes toward IoT adoption. The usability of IoT systems plays a crucial role in adoption. Farmers who find IoT easy to use are more inclined to exhibit a favorable perspective, reinforcing the importance of designing intuitive technologies.
- While the conceptual model includes other variables such as Optimism, Innovativeness, Discomfort, and others, this study specifically did not test their direct influence on Attitude Toward IoT. Therefore, these findings do not provide a conclusion on the influence of these variables, but rather confirm that PU and PEOU serve as the principal predictors of IoT adoption among rice farmers based on the scope and focus of this research.

### B. Implications for IoT Adoption in Agriculture

- Emphasizing Benefits and Ease of Use, IoT adoption initiatives should clearly communicate practical benefits, such as increased productivity, cost savings, and time efficiency, while ensuring technology remains accessible and easy to use.
- User-Centered IoT Development IoT systems should incorporate intuitive interfaces and provide adequate training, enabling farmers to seamlessly integrate technology into their agricultural practices.
- Future Research Directions: Further studies should explore contextual factors, such as social norms, cultural influences, policy frameworks, and peer networks, which may shape farmers' attitudes toward IoT adoption.

### C. Final Conclusion

This study concludes that rice farmers' attitudes toward IoT adoption are primarily shaped by PU and PEOU, highlighting the need for user-centric technological interventions in agriculture. Therefore, successful IoT implementation in agriculture must prioritize solutions that deliver clear benefits while remaining user-friendly. By ensuring accessibility and demonstrating tangible advantages, technology developers and policymakers can create an environment that fosters IoT adoption and enhances farming productivity.

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