



A Contextual Framework for Agricultural IoT Adoption: Integrating TAM, Innovation–Decision Process, and Governmental Support in Smart Farming Contexts

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Abstract: Agricultural Internet of Things (IoT) adoption in developing contexts remains constrained by a fragmented understanding of cognitive, behavioral, and contextual factors. A contextual framework is developed by integrating the Technology Acceptance Model (TAM), selected components of the Innovation–Decision Process (IDP), and key enabling conditions to explain continued use intention in smart farming environments. Data from 250 Thai agricultural stakeholders with prior exposure to or implementation experience with IoT-based agricultural applications were analyzed using partial least squares structural equation modeling (PLS-SEM). Results indicate that perceived usefulness is the strongest predictor of attitude toward use, which in turn drives continued use intention. Knowledge plays a critical role as a precursor, shaping perceived ease of use, persuasion, and perceived usefulness, underscoring the importance of cognitive readiness even among experienced users. Facilitating conditions significantly support continued use intention, whereas governmental support shows no direct effect. Perceived ease of use does not significantly influence attitude, suggesting that functional value may outweigh usability considerations in post-adoption or experience-based contexts. The framework offers a context-sensitive explanation of agricultural IoT adoption by linking cognitive processes with operational support mechanisms, while the model-fit results indicate that conclusions should be interpreted with appropriate caution.

Keywords: Agricultural Internet of things; smart farming; technology acceptance model; innovation–decision process; continued use intention

1. Introduction

Global agriculture is undergoing rapid transformation driven by advanced digital technologies, particularly the Internet of Things (IoT). In agricultural contexts, IoT systems enable real-time monitoring and automated management through integrated sensor networks, data analytics, and cloud platforms. These capabilities support precision irrigation, soil assessment, pest detection, and remote farm supervision, thereby enhancing productivity, resource efficiency, and sustainability [1-3].

In Thailand, the Ministry of Agriculture and Cooperatives has introduced the “Digital Agriculture Development Plan (2021–2027)” to accelerate the adoption of smart technologies. Despite these national initiatives,

adoption among smallholder farmers remains limited, particularly in rural areas characterized by insufficient connectivity and support services. A nationwide survey by the Digital Economy Promotion Agency indicates that fewer than 25% of farmers have implemented IoT technologies, largely due to technological complexity, infrastructural gaps, and limited access to training and financial support [4]. These constraints suggest that technology availability alone does not necessarily lead to successful adoption outcomes in resource-constrained environments. From a technical perspective, prior studies demonstrate that IoT-based smart agriculture systems enable data-driven decision-making and automation through architectures integrating sensor nodes, microcontrollers, communication protocols (e.g., MQTT and HTTP), cloud platforms, and user interfaces. Empirical evidence has been reported across applications such as precision irrigation and water-use efficiency improvement [5, 6], low-power sensor-based irrigation automation [7, 8], and greenhouse monitoring using real-time environmental data and dashboards [9, 10]. Research also highlights cost-effective, modular approaches that improve accessibility in smallholder and peri-urban farming contexts [11, 12].

Recent developments further demonstrate the integration of artificial intelligence (AI) with IoT to enhance agricultural monitoring and decision support. For example, an AI-driven smart farming system combining environmental sensing with image-based plant health analysis has demonstrated improved accuracy in detecting nutrient deficiencies and enabling automated responses in real-world deployments [13]. Similarly, IoT-based automation in livestock environments has shown the ability to monitor environmental conditions and optimize operational efficiency, including reductions in mortality rates and improvements in farm productivity [14]. Related IoT-enabled systems in laboratory education, healthcare monitoring, and smart-learning contexts further illustrate the broader regional diffusion of IoT applications and the need to understand user readiness and contextual support across applied domains [15-18]. These developments reinforce the practical potential of IoT-enabled systems while highlighting the importance of system integration, real-time control, and user interaction in agricultural applications.

Comprehensive reviews highlight ongoing trends toward interoperability, energy efficiency, and scalable platform design, while also emphasizing persistent deployment challenges such as sensor calibration, unreliable connectivity, and limited user readiness [19, 20]. System-level perspectives emphasize the importance of modularity and scalability in IoT ecosystems [21], whereas cross-sector insights indicate that institutional support and platform readiness function as critical enabling conditions for adoption in developing economies [22]. Successful deployment and sustained use depend not only on technical feasibility but also on user acceptance and decision-making processes. Behavioral and contextual factors—such as perceived usefulness (PU), perceived ease of use (PEOU), social influence, and institutional support—play a central role in determining whether available technologies are used [5, 6]. Consequently, adoption research has relied extensively on theoretical models to explain how users form attitudes and intentions toward smart farming technologies.

Among these models, the Technology Acceptance Model (TAM) proposed by Davis [23] remains widely applied, with perceived usefulness and perceived ease of use consistently identified as key predictors of attitude and behavioral intention. Empirical evidence across agricultural and related domains supports the robustness of TAM relationships, while also revealing contextual variability across user groups and environments [24-28]. To better capture real-world complexity, researchers have extended TAM by incorporating complementary frameworks such as UTAUT, TOE, and innovation diffusion theory. These hybrid approaches highlight enabling conditions and governmental support as structural determinants that may either facilitate or constrain adoption, particularly in smallholder farming contexts [6, 29-32]. Broader synthesis studies further suggest that agricultural technology adoption is a socio-technical process that requires alignment across economic, organizational, and infrastructural dimensions [33, 34].

Regional evidence underscores the context-dependent nature of agricultural IoT adoption. Studies conducted in Thailand and Southeast Asia emphasize the role of institutional facilitation and policy support [24, 31, 32], whereas findings from China highlight technological complexity and organizational readiness [30, 35]. Research in Nepal identifies self-efficacy and anxiety as critical psychological determinants [27], while studies

in Sub-Saharan Africa emphasize systemic barriers and the importance of trust and actual use considerations [36]. A scoping review across low- and middle-income contexts consistently reports challenges related to high costs, limited digital literacy, insufficient training, and weak technical support infrastructures [37]. Collectively, these findings indicate that agricultural IoT adoption models must incorporate both behavioral determinants and contextual enablers to reflect real-world conditions accurately.

Despite these advances, several research gaps remain. Existing studies predominantly emphasize behavioral intention while paying limited attention to process-based dynamics and early-stage cognitive determinants that shape user perceptions before adoption. In addition, contextual factors such as governmental support and infrastructural readiness are often acknowledged but not consistently operationalized within unified analytical frameworks. Empirical evidence focusing on Thai users with direct agricultural IoT experience also remains limited. These gaps highlight the need for a context-sensitive, empirically grounded, and process-oriented framework that integrates behavioral beliefs, cognitive stages, and external enabling mechanisms.

Accordingly, a hybrid framework is proposed and empirically validated by integrating the Technology Acceptance Model (TAM) with selected components of Rogers' Innovation–Decision Process (IDP), while explicitly incorporating facilitating conditions and governmental support as contextual enablers. Quantitative data from 250 Thai agricultural IoT stakeholders with prior exposure to or implementation experience with agricultural IoT applications were analyzed using partial least squares structural equation modeling (PLS-SEM), providing empirical insights into how cognitive, behavioral, and contextual factors jointly shape adoption and continued use intention in smart farming contexts.

2. Materials and Methods

A quantitative research approach underpins the empirical examination of agricultural Internet of Things (IoT) adoption and continued use among Thai agricultural stakeholders. Methodological design follows a hypothetico-deductive paradigm, integrating behavioral, cognitive, and contextual perspectives to evaluate the proposed framework. Structural equation modeling (SEM) is employed as the primary analytical technique, enabling simultaneous assessment of measurement validity and structural relationships among latent constructs.

2.1 Conceptual Framework and Hypotheses Development

Integration of the Technology Acceptance Model (TAM) with selected components of Rogers' Innovation–Decision Process (IDP) underpins the proposed conceptual framework, complemented by two contextual enablers: facilitating conditions (FC) and governmental support (GS). Framework design seeks to explain agricultural Internet of Things (IoT) adoption and continued use by capturing interactions among early-stage cognitive processes, perceived system value, and external support mechanisms within resource-constrained farming contexts. Within this structure, TAM provides the core behavioral foundation through perceived ease of use (PEOU) and perceived usefulness (PU), both of which shape attitude toward use (ATT) and subsequently influence behavioral intention (BI) [38]. In the present study, behavioral intention reflects continued use intention, emphasizing sustained engagement with IoT technologies among respondents with prior experience. To extend explanatory capacity beyond conventional TAM, two constructs derived from the Innovation–Decision Process (IDP)—knowledge (KN) and persuasion (PS)—are incorporated to represent early-stage cognitive dynamics preceding attitude formation. Knowledge captures awareness and understanding of agricultural IoT technologies, whereas persuasion reflects evaluative influence shaped by communication, social interaction, and perceived relevance during initial exposure and early adoption phases [39]. The selection of these constructs aligns with cognitive and evaluative stages of innovation processing, which remain particularly relevant in cross-sectional analyses focusing on user perception rather than longitudinal adoption trajectories.

Contextual influences are represented through two external enabling mechanisms. Facilitating conditions capture perceived availability of infrastructure, technical support, and training necessary for

effective IoT utilization at the operational level [6]. Governmental support reflects policy initiatives, financial incentives, and extension services designed to reduce adoption barriers and enhance readiness for digital agriculture [40, 41]. Within the proposed framework, governmental support is conceptualized as a macro-level contextual driver, whereas facilitating conditions operate at a more immediate and operational level of technology use. This configuration is intended to extend conventional TAM-based adoption models in three ways. First, knowledge and persuasion are selected from the IDP because they represent the cognitive and evaluative stages most directly observable in a cross-sectional perception study; later IDP stages, such as decision, implementation, and confirmation, require stronger longitudinal evidence. Second, persuasion is modeled as an evaluative mechanism shaped by peer communication, community influence, and perceived relevance, allowing it to directly affect attitude while also being tested for its direct influence on continued use intention. Third, governmental support is modeled as a direct antecedent of behavioral intention to examine whether policy-level support is visible enough to shape users' intentions beyond immediate facilitating conditions. This arrangement therefore tests whether cognitive readiness, technology beliefs, and contextual support mechanisms jointly enhance explanatory value in a Thai smart farming context. Figure 1 illustrates the integrated conceptual framework, highlighting hypothesized relationships among cognitive, behavioral, and contextual constructs. Knowledge influences perceived ease of use, perceived usefulness, and persuasion (H1–H3), while persuasion contributes to both attitude and behavioral intention (H4–H5). Perceived ease of use affects perceived usefulness and attitude (H6–H7), whereas perceived usefulness and persuasion jointly shape attitude (H8). Attitude subsequently determines behavioral intention (H9), while facilitating conditions and governmental support are modeled as direct predictors of behavioral intention (H10–H11).

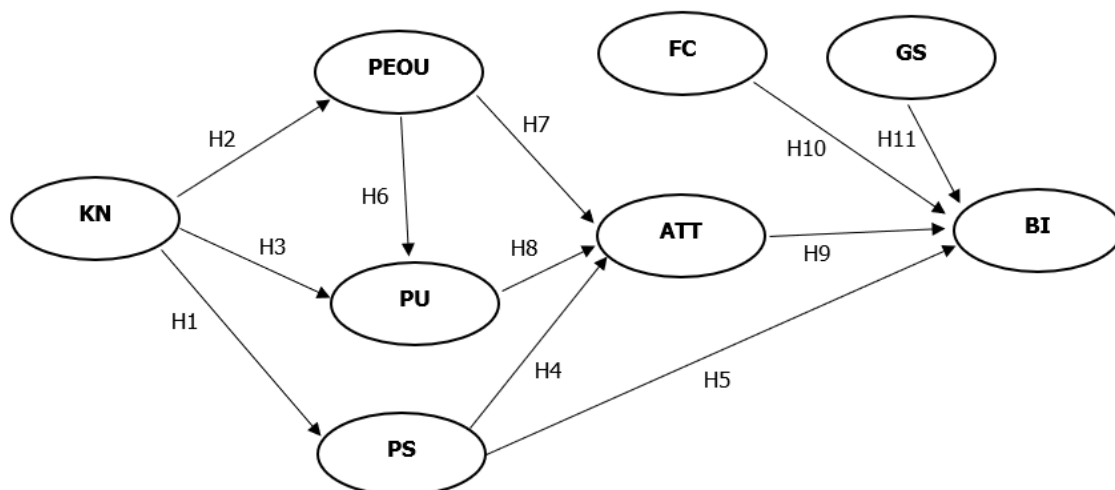


Figure 1. Conceptual framework for agricultural IoT adoption and continued use. *KN = Knowledge; PS = Persuasion; PEOU = Perceived Ease of Use; PU = Perceived Usefulness; ATT = Attitude toward Use; BI = Behavioral Intention; FC = Facilitating Conditions; GS = Governmental Support*

Empirical evaluation is conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is well-suited for complex models involving multiple latent constructs and predictive-oriented research objectives. This approach enables simultaneous estimation of direct and indirect effects, providing a comprehensive understanding of how cognitive, behavioral, and contextual factors jointly shape agricultural IoT adoption and continued use.

2.2 Research Objectives

Building on the integrated conceptual framework, this study addresses the following research objectives:

1. Examination of the effects of perceived usefulness (PU) and perceived ease of use (PEOU) on attitude toward use (ATT) and continued behavioral intention (BI), to assess the applicability of the Technology Acceptance Model in agricultural IoT contexts.

2. Investigation of how cognitive factors derived from the Innovation–Decision Process—specifically knowledge (KN) and persuasion (PS)—shape early-stage awareness, evaluation, and attitudinal development associated with agricultural IoT adoption.
3. Evaluation of the influence of contextual enablers, namely facilitating conditions (FC) and governmental support (GS), on continued behavioral intention toward agricultural IoT use in resource-constrained environments.

2.3 Research Hypotheses

Grounded in the proposed conceptual framework, eleven hypotheses are specified to examine relationships among cognitive determinants, technology acceptance constructs, and contextual influences shaping agricultural Internet of Things (IoT) adoption and continued use.

2.3.1 Cognitive Determinants (Innovation-Decision Process)

Cognitive factors derived from the Innovation–Decision Process capture early-stage awareness and evaluative mechanisms that precede attitude formation. Knowledge is expected to strengthen persuasion while also shaping perceptions of system usability and usefulness. Accordingly:

- H1: Knowledge (KN) positively influences persuasion (PS).
- H2: Knowledge (KN) positively influences perceived ease of use (PEOU).
- H3: Knowledge (KN) positively influences perceived usefulness (PU).

Persuasion reflects evaluative influence shaped by communication and social interaction and is expected to contribute to both attitudinal responses and continued behavioral intentions toward technology use. Thus:

- H4: Persuasion (PS) positively influences attitude toward use (ATT).
- H5: Persuasion (PS) positively influences continued behavioral intention (BI).

2.3.2 Technology Acceptance Constructs

Relationships among perceived ease of use, perceived usefulness, attitude, and behavioral intention follow the core structure of the Technology Acceptance Model. Perceived ease of use enhances perceived usefulness and contributes to attitude formation, while perceived usefulness reinforces positive attitudes that drive continued intention. Accordingly:

- H6: Perceived ease of use (PEOU) positively influences perceived usefulness (PU).
- H7: Perceived ease of use (PEOU) positively influences attitude toward use (ATT).
- H8: Perceived usefulness (PU) positively influences attitude toward use (ATT).
- H9: Attitude toward use (ATT) positively influences continued behavioral intention (BI).

2.3.3 Contextual Determinants

Contextual influences represent external conditions that shape technology use beyond individual perception. Facilitating conditions are expected to directly support continued use through operational resources and infrastructure, while governmental support reflects broader institutional mechanisms that may influence intention formation. Accordingly:

- H10: Facilitating conditions (FC) positively influence continued behavioral intention (BI).
- H11: Governmental support (GS) positively influences continued behavioral intention (BI).

Table 1 summarizes the proposed hypotheses and their theoretical foundations.

Table 1. Constructs and Associated Hypotheses

Hypothesis	Source Construct	Target Construct	Framework
H1	Knowledge (KN)	Persuasion (PS)	IDP
H2	Knowledge (KN)	Perceived ease of use (PEOU)	IDP
H3	Knowledge (KN)	Perceived usefulness (PU)	IDP
H4	Persuasion (PS)	Attitude toward use (ATT)	IDP
H5	Persuasion (PS)	Continued behavioral intention (BI)	IDP
H6	Perceived ease of use (PEOU)	Perceived usefulness (PU)	TAM
H7	Perceived ease of use (PEOU)	Attitude toward use (ATT)	TAM
H8	Perceived usefulness (PU)	Attitude toward use (ATT)	TAM
H9	Attitude toward use (ATT)	Continued behavioral intention (BI)	TAM
H10	Facilitating conditions (FC)	Continued behavioral intention (BI)	Contextual
H11	Governmental support (GS)	Continued behavioral intention (BI)	Contextual

2.4 Research Design

A cross-sectional quantitative design underpins data collection using a structured questionnaire administered to Thai agricultural stakeholders with direct experience in agricultural IoT technologies. The design choice supports the statistical validation of relationships among latent constructs derived from the Technology Acceptance Model (TAM), the Innovation–Decision Process (IDP), and contextual adoption perspectives. Structural equation modeling is adopted as the primary analytical approach due to its capacity to simultaneously evaluate measurement reliability and validity, account for measurement error, and estimate complex structural relationships among constructs.

2.5 Sample and Data Collection

The target population comprises Thai agricultural stakeholders with prior exposure to or experience implementing IoT-based agricultural applications, including automated irrigation systems, environmental monitoring sensors, and digital farm management platforms. The term “stakeholders” is used deliberately because smart farming adoption in Thailand involves not only farm owners and direct users but also agricultural officers, extension personnel, technology service providers, private-sector practitioners, and organizational actors who support implementation. Therefore, the study does not claim to represent farmers exclusively; rather, it captures perceptions within the broader agricultural IoT adoption ecosystem. Data collection was conducted using a standardized questionnaire distributed through both online and offline channels. Offline administration was supported by agricultural extension officers and farming cooperatives, whereas online distribution leveraged smart agriculture networks and social media platforms. Screening questions were used to ensure that participants had direct familiarity with agricultural IoT applications, either through personal use, implementation support, technical operation, advisory roles, or institutional involvement. This mixed-mode approach improved geographical and role-based coverage, particularly across rural and remote areas. Recommended minimum sample size for structural equation modeling exceeds 200 observations [42]. The final dataset comprises 250 valid responses, meeting commonly accepted thresholds for model estimation and statistical power. Ethical approval is obtained prior to data collection, and informed consent is obtained from all participants.

2.6 Measurement Instrument

Data collection is conducted using a structured questionnaire comprising two sections. The first section captures demographic characteristics to contextualize respondent profiles. The second section measures eight latent constructs derived from the proposed framework: knowledge (KN), persuasion (PS), perceived ease of use (PEOU), perceived usefulness (PU), attitude toward use (ATT), continued behavioral intention (BI), facilitating conditions (FC), and governmental support (GS). Measurement items were adapted from established and validated scales, including Davis [23], Rogers [39], and Venkatesh et al. [43], and

subsequently modified to reflect the agricultural IoT context. Construct wording was reviewed to ensure relevance to smart farming applications such as sensor-based monitoring, irrigation automation, and digital farm management. All constructs were operationalized as reflective measures using three to five items per construct. Responses were recorded on a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). Item codes, adapted item content, source references, and outer loadings are provided in Supplementary Table S1. Content validity is established through expert evaluation involving three domain specialists in agricultural technology and information systems. Pilot testing involving 30 smart farming practitioners is conducted to assess clarity, wording, and contextual relevance. Feedback from the pilot phase is incorporated to refine the measurement instrument before full-scale data collection. Construct definitions are summarized in Table 2, while detailed measurement items and corresponding factor loadings are provided in the supplementary materials.

Table 2. Construct Definitions

Construct	Definition
Knowledge (KN)	Understanding of IoT functionality and its applications in agriculture.
Persuasion (PS)	Influence of peers and community on acceptance of IoT.
Perceived ease of use (PEOU)	The degree to which IoT systems are perceived as easy to operate.
Perceived usefulness (PU)	The extent to which IoT use is seen as beneficial to farming.
Attitude toward use (ATT)	Users' affective evaluation of using IoT technologies.
Continued behavioral intention (BI)	Intention to continue using and engaging with IoT systems in agricultural operations.
Facilitating conditions (FC)	Availability of infrastructure and technical support for IoT.
Governmental support (GS)	Perceived support from the government in adopting IoT technologies.

Common method bias was mitigated through procedural remedies, including anonymity assurance, neutral wording of questionnaire items, separation of construct blocks, and clarification that there were no right or wrong answers. In addition, post hoc diagnostics were conducted. Harman's single-factor test indicated that the first unrotated factor did not account for a majority of the total variance, and the structural collinearity assessment showed that VIF values remained below the conservative threshold of 3.3. These results suggest that common method variance is unlikely to substantially bias the findings, although the cross-sectional self-report design remains a limitation.

2.7 Data Analysis

A variance-based PLS-SEM approach is applied to evaluate the proposed framework [42]. The first stage focuses on assessing the measurement model, including internal consistency reliability, convergent validity, and discriminant validity. Reliability is examined using Cronbach's alpha and composite reliability (CR), with values above 0.70 indicating acceptable internal consistency [44]. Convergent validity is assessed using average variance extracted (AVE), with a threshold of 0.50 [45]. Discriminant validity is evaluated using the Fornell–Larcker criterion and the heterotrait–monotrait (HTMT) ratio, where values below 0.90 indicate adequate discriminant validity [46]. The second stage evaluates the structural model by estimating path coefficients, t-values, p-values, confidence intervals, effect sizes (f^2), and inner VIF values obtained through bootstrapping with 5,000 resamples. VIF values are examined to assess potential collinearity among predictor constructs. Model explanatory power and predictive relevance are assessed using the coefficient of determination (R^2), effect size (f^2), and Stone–Geisser's Q^2 . Model fit is examined using the standardized root mean square residual (SRMR), while acknowledging that SRMR is a diagnostic indicator rather than a sole acceptance criterion in predictive-oriented PLS-SEM. Key evaluation criteria are summarized in Table 3.

Table 3. Model Fit Criteria

Fit Index	Threshold
SRMR	< 0.08 (commonly recommended guideline)
Cronbach's Alpha	≥ 0.70
Composite Reliability (CR)	≥ 0.70
Average Variance Extracted (AVE)	≥ 0.50
Fornell–Larcker Criterion	The square root of AVE exceeds inter-construct correlations
HTMT Ratio	< 0.90
R ²	≥ 0.10 (minimum acceptable level)
Q ²	> 0.00 (predictive relevance)
f ²	≥ 0.02 (small effect size)

Note: Threshold values are based on commonly recommended guidelines in PLS-SEM literature and should be interpreted with caution depending on model context.

3. Results and Discussion

This section presents and interprets the empirical findings derived from the structural equation modeling analysis. Results are discussed in relation to the proposed hypotheses and relevant theoretical perspectives, integrating statistical evidence with prior research to explain agricultural Internet of Things (IoT) adoption and continued use in resource-constrained contexts.

3.1 Respondent Profile and Descriptive Overview

A total of 250 valid responses from Thai agricultural stakeholders with direct experience in or close involvement with agricultural IoT technologies are included in the analysis, as summarized in Table 4. Male participants constitute the majority (95.6%), while the largest age group falls between 45–54 years (48.4%), indicating a mature user base. Educational attainment is relatively high, with most respondents holding at least a bachelor's degree (57.1%), suggesting sufficient capacity to engage with digital technologies. Occupational distribution extends beyond farmers, with substantial representation from government or state enterprises (39.6%) and the private sector (26.4%), as well as business owners and other roles. This profile indicates that the sample represents a mixed group of agricultural IoT stakeholders rather than farmers alone. Many respondents were involved in implementation, advisory, technical support, extension, or organizational decision-making activities related to smart farming. Accordingly, the findings should be interpreted as reflecting stakeholder-based continued use intention within the agricultural IoT ecosystem, not as a population estimate of Thai farmers as a whole.

Table 4. Demographic Profile of Respondents (N = 250)

Variable	Category	Percentage (%)
Gender	Male	95.6
	Female / Other	4.4
Age	Below 25 years	3.0
	25–34 years	12.1
	35–44 years	23.1
	45–54 years	48.4
	55 years and above	13.2
Education Level	Secondary school	5.5
	Vocational diploma (Voc. Cert. / High Voc.)	2.2
	Bachelor's degree	57.1
	Postgraduate degree	35.2
Occupation	Farmer	11.0
	Government/State enterprise employee	39.6
	Private sector employee	26.4
	Business owner	11.0
	Other	12.1

Observed demographic patterns suggest a stakeholder composition aligned with early adoption of smart farming technologies in Thailand, where institutional and public-sector channels play a central role in technology diffusion. This context provides a critical lens for interpreting subsequent behavioral and contextual effects, particularly the influence of external support mechanisms on continued technology use.

3.2 Measurement Model Results

The measurement model is evaluated before structural analysis to ensure adequate reliability and validity of the latent constructs. The assessment focuses on internal consistency reliability, convergent validity, and discriminant validity, following the established PLS-SEM procedure.

3.2.1 Internal Consistency and Convergent Validity

Internal consistency reliability is assessed using Cronbach's alpha and composite reliability (CR). All constructs exceed the recommended threshold of 0.70, indicating satisfactory reliability. Convergent validity is evaluated using average variance extracted (AVE) and indicator loadings. Most constructs achieve AVE values above 0.50, while outer loadings are generally above 0.70, supporting adequate convergent validity and strong indicator reliability. A marginal deviation is observed for persuasion (PS), where AVE falls slightly below the recommended threshold (AVE = 0.482). This construct was retained for three reasons. First, Cronbach's alpha and composite reliability exceed acceptable levels, indicating adequate internal consistency. Second, most indicators show acceptable loadings, while the lower-loading item reflects the social-communication dimension of persuasion that is theoretically central to the Innovation–Decision Process. Third, removing the item would narrow the conceptual domain of persuasion and reduce content validity. Consequently, PS is retained but interpreted cautiously, especially for paths involving behavioral intention. Detailed results, including Cronbach's alpha, composite reliability, AVE, and indicator loadings, are presented in Table 5.

Table 5. Measurement Model Results: Reliability and Convergent Validity

Construct	Cronbach's α	Composite Reliability (CR)	AVE	Loading Range
ATT	0.949	0.961	0.833	0.829 – 0.970
BI	0.956	0.966	0.850	0.898 – 0.945
FC	0.837	0.883	0.601	0.720 – 0.844
GS	0.932	0.949	0.788	0.796 – 0.949
KN	0.937	0.953	0.803	0.806 – 0.956
PEOU	0.919	0.940	0.759	0.780 – 0.947
PS	0.773	0.818	0.482	0.533 – 0.860
PU	0.937	0.952	0.800	0.840 – 0.921

3.2.2 Discriminant Validity

Discriminant validity is evaluated using the Fornell–Larcker criterion. Results show that the square roots of the AVEs for each construct exceed their correlations with other constructs, indicating adequate discriminant validity across the measurement model. Moderate correlations observed among selected constructs (e.g., ATT and BI) remain within acceptable limits and reflect expected theoretical relationships rather than measurement overlap. Detailed results are presented in Table 6.

Table 6. Discriminant Validity Assessment (Fornell–Larcker Criterion)

Construct	ATT	BI	FC	GS	KN	PEOU	PS	PU
ATT	0.913							
BI	0.768	0.922						
FC	0.479	0.565	0.775					
GS	0.372	0.359	0.591	0.888				
KN	0.511	0.554	0.550	0.366	0.896			
PEOU	0.552	0.471	0.583	0.391	0.685	0.871		
PS	0.589	0.495	0.454	0.592	0.467	0.467	0.695	
PU	0.787	0.615	0.578	0.442	0.566	0.704	0.579	0.894

Further assessment of discriminant validity is conducted using the heterotrait–monotrait (HTMT) ratio. All HTMT values remain below the recommended threshold of 0.90, supporting adequate discriminant validity across constructs. The highest HTMT value is observed between attitude toward use (ATT) and perceived usefulness (PU), reflecting a strong conceptual relationship while remaining within acceptable limits. These results confirm that the constructs are empirically distinct despite their theoretical interrelatedness. Detailed HTMT results are presented in Table 7.

Table 7. Discriminant Validity Assessment (HTMT Ratios)

Construct	ATT	BI	FC	GS	KN	PEOU	PS	PU
ATT								
BI	0.805							
FC	0.512	0.600						
GS	0.392	0.371	0.678					
KN	0.536	0.586	0.626	0.389				
PEOU	0.589	0.500	0.657	0.422	0.732			
PS	0.538	0.435	0.576	0.768	0.536	0.478		
PU	0.832	0.647	0.638	0.468	0.596	0.756	0.566	

3.3 Structural Model Results and Hypothesis Testing

Hypothesis testing was conducted using a bootstrapping procedure with 5,000 resamples to evaluate the significance of the proposed structural relationships. Standardized path coefficients (β), t-values, p-values, effect sizes (f^2), and VIF values are reported in Table 8. All reported VIF values remain below the commonly recommended threshold, indicating that collinearity among predictor constructs is not a major concern.

Table 8. Structural Path Coefficients, Collinearity Diagnostics, and Hypothesis Testing Results

Hypothesis	Path	β	t-value	p-value	f^2	Result	VIF	95% CI
H1	KN $\rightarrow$ PS	0.467	6.820	< 0.001	0.278	Supported	1.000	[0.333, 0.601]
H2	KN $\rightarrow$ PEOU	0.685	17.934	< 0.001	0.885	Supported	1.000	[0.610, 0.760]
H3	KN $\rightarrow$ PU	0.157	2.141	0.037	0.027	Supported	1.885	[0.013, 0.301]
H4	PS $\rightarrow$ ATT	0.203	4.561	< 0.001	0.077	Supported	1.558	[0.116, 0.290]
H5	PS $\rightarrow$ BI	0.026	0.398	0.637	0.001	Not Supported	1.617	[-0.102, 0.154]
H6	PEOU $\rightarrow$ PU	0.597	8.051	< 0.001	0.385	Supported	1.885	[0.452, 0.742]
H7	PEOU $\rightarrow$ ATT	-0.029	0.552	0.553	0.001	Not Supported	2.259	[-0.132, 0.074]
H8	PU $\rightarrow$ ATT	0.689	12.888	< 0.001	0.570	Supported	2.444	[0.584, 0.794]
H9	ATT $\rightarrow$ BI	0.640	11.427	< 0.001	0.676	Supported	1.678	[0.530, 0.750]
H10	FC $\rightarrow$ BI	0.284	4.890	< 0.001	0.129	Supported	1.584	[0.170, 0.398]
H11	GS $\rightarrow$ BI	-0.062	1.272	0.210	0.006	Not Supported	1.626	[-0.158, 0.034]

Results indicate that several hypothesized relationships are statistically supported. Perceived usefulness (PU) exerts a strong positive effect on attitude toward use (ATT) ($\beta = 0.689$, $t = 12.888$, $p < 0.001$), confirming its central role in shaping users' evaluations of agricultural IoT technologies. Attitude toward use subsequently demonstrates a strong positive effect on continued behavioral intention (BI) ($\beta = 0.640$, $t = 11.427$, $p < 0.001$), reinforcing its critical role in sustained technology adoption. Persuasion (PS) significantly influences attitude ($\beta = 0.203$, $t = 4.561$, $p < 0.001$), indicating that social and evaluative processes contribute to attitude formation. Facilitating conditions (FC) also show a significant positive effect on behavioral intention ($\beta = 0.284$, $t = 4.890$, $p < 0.001$), highlighting the importance of infrastructure and technical support. In contrast, governmental support (GS) does not exhibit a significant direct effect on behavioral intention ($\beta = -0.062$, $t = 1.272$, $p = 0.210$), suggesting a potential gap between policy-level initiatives and user-perceived support. Similarly, persuasion does not significantly influence behavioral intention ($\beta = 0.026$, $t = 0.398$, $p = 0.637$), indicating that its effect is

primarily indirect. Perceived ease of use (PEOU) does not significantly influence attitude ($\beta = -0.029$, $t = 0.552$, $p = 0.553$), suggesting that usability plays a limited role in post-adoption contexts. However, PEOU significantly influences perceived usefulness ($\beta = 0.597$, $t = 8.051$, $p < 0.001$), consistent with TAM. Knowledge (KN) significantly influences perceived ease of use ($\beta = 0.685$, $t = 17.934$, $p < 0.001$), persuasion ($\beta = 0.467$, $t = 6.820$, $p < 0.001$), and perceived usefulness ($\beta = 0.157$, $t = 2.141$, $p = 0.037$), confirming its foundational role in shaping early-stage perceptions.

3.4 Model Explanatory Power and Predictive Relevance

Explanatory power is assessed using the coefficient of determination (R^2), representing the proportion of variance explained in each endogenous construct. As shown in Table 9, the model demonstrates strong explanatory capability for the key outcome variables. Attitude toward use (ATT) and behavioral intention (BI) exhibit high R^2 values of 0.646 and 0.643, respectively, indicating that the integrated framework explains a substantial proportion of the variance in users' attitudinal and behavioral intentions toward agricultural IoT adoption.

Table 9. Coefficient of determination (R^2).

Construct	R^2	Adjusted R^2
ATT	0.646	0.642
BI	0.643	0.637
PEOU	0.470	0.467
PS	0.218	0.215
PU	0.509	0.505

Perceived usefulness (PU) and perceived ease of use (PEOU) present moderate explanatory power ($R^2 = 0.509$ and 0.470), while persuasion (PS) shows a lower yet acceptable level of explained variance ($R^2 = 0.218$), consistent with its role as an early-stage cognitive construct. Model fit is further evaluated using the standardized root mean square residual (SRMR). The SRMR values are 0.090 for the saturated model and 0.135 for the estimated model, both exceeding the commonly suggested threshold of 0.08. This indicates that the model does not fully meet conventional model-fit criteria. Therefore, the results should be interpreted with caution, and SRMR is treated as a limitation of the study. Accordingly, model interpretation relies on a combination of explanatory and predictive metrics, including R^2 and Q^2 , rather than SRMR alone. Predictive relevance is assessed using the blindfolding procedure, which yields the cross-validated redundancy measure (Q^2). A Q^2 value greater than zero indicates predictive capability. As reported in Table 10, all endogenous constructs demonstrate Q^2 values above zero, confirming the model's predictive relevance. Behavioral intention ($Q^2 = 0.401$) and attitude toward use ($Q^2 = 0.356$) exhibit strong predictive power, while perceived usefulness and perceived ease of use show moderate predictive relevance. Persuasion, although lower in magnitude, remains meaningful in capturing early-stage evaluative processes within the adoption mechanism. Overall, the combined evidence from R^2 and Q^2 assessments suggests that the integrated TAM-IDP framework provides meaningful explanatory and predictive relevance for key endogenous constructs. However, the elevated SRMR values indicate that the model should be interpreted as a useful but not definitive representation of agricultural IoT adoption. Additional statistics, including effect sizes, indirect effects, item-level measurement diagnostics, and supplementary predictive diagnostics, are provided in Supplementary Tables S1–S4.

Table 10. Predictive relevance (Q^2).

Construct	Q^2 Value
Behavioral intention (BI)	0.401
Attitude toward use (ATT)	0.356
Perceived usefulness (PU)	0.291
Perceived ease of use (PEOU)	0.243
Persuasion (PS)	0.198

Note: Q^2 values greater than zero indicate the model's predictive relevance.

3.5 Integrated Discussion

Findings provide empirical support for the usefulness of the integrated TAM-IDP framework in explaining agricultural IoT adoption. Perceived usefulness (PU) and attitude toward use (ATT) emerge as the most influential determinants of continued behavioral intention (BI), confirming that perceived value remains the primary driver of adoption decisions. This pattern aligns with prior TAM-based studies, which show that functional benefits outweigh other considerations in shaping user acceptance, particularly in task-oriented and outcome-driven environments. The non-significant effect of perceived ease of use (PEOU) on attitude suggests that usability considerations become less salient once users have experience with agricultural IoT technologies. In post-adoption or experience-based contexts, users may evaluate systems less by simplicity and more by whether the technology produces tangible operational benefits such as improved monitoring, reduced labor, or better farm decisions. The significant PEOU → PU path supports this interpretation: ease of use appears to matter indirectly by strengthening perceived usefulness rather than directly shaping attitude.

Integration of knowledge (KN) and persuasion (PS) from the Innovation–Decision Process provides additional explanatory depth by capturing early-stage cognitive dynamics. Knowledge significantly influences perceived ease of use, perceived usefulness, and persuasion, highlighting its foundational role in shaping users' mental models of technology. Persuasion contributes to attitude formation but does not directly influence behavioral intention, indicating that peer communication and evaluative influence may first shape favorable attitudes before becoming behavioral commitment. This finding supports a mediated interpretation of persuasion rather than a simple direct-intention mechanism. Facilitating conditions (FC) have a significant positive effect on behavioral intention, underscoring the roles of infrastructure, training, and technical support in enabling adoption. In contrast, governmental support (GS) does not exhibit a significant direct effect, suggesting a disconnect between policy-level initiatives and users' perceived or experienced support. Several explanations are plausible: policy support may be unevenly visible to users, may operate indirectly through facilitating conditions, or may be perceived as too general to influence day-to-day technology decisions. Future studies should test mediation or moderation mechanisms linking governmental support to more immediate operational enablers. Collectively, the integration of cognitive, behavioral, and contextual dimensions offers a comprehensive explanation of IoT adoption in resource-constrained agricultural environments. Results highlight that successful digital transformation in agriculture requires more than technological functionality; it depends on informed users, effective knowledge dissemination, and operational support systems that translate institutional intent into practical adoption.

4. Limitations and Future Research

Several limitations should be acknowledged. First, the study uses a cross-sectional survey design; therefore, the findings support associative interpretation rather than strong causal claims. Longitudinal research is needed to examine how knowledge, persuasion, attitude, and continued use intention evolve across the full innovation-decision process. Second, the sample represents agricultural IoT stakeholders rather than farmers exclusively. Although this broader stakeholder perspective is appropriate for smart farming ecosystems, it limits the extent to which findings can be generalized to the wider population of Thai farmers. Future studies should compare farmers, extension officers, technology providers, and policy actors as separate groups. Third, all variables were measured using self-reported questionnaire data collected at one point in time. Procedural and statistical checks suggest that common method bias is unlikely to dominate the results, but it cannot be fully eliminated. Future research should incorporate objective usage data, field observations, or multi-source measures. Fourth, the persuasion construct has an AVE value slightly below the recommended threshold, and the SRMR values exceed the common guideline. These issues indicate that the model should be interpreted cautiously and may benefit from further refinement of the measurements. Future studies should test alternative item specifications, additional contextual mediators, and multi-group comparisons across regions and farm types. Finally, governmental support was modeled as a direct predictor of continued use intention. The non-significant result suggests that policy-level support may operate indirectly by facilitating conditions, improving access to training, enhancing perceived affordability, or fostering trust. Future research should examine these mediating pathways and evaluate the effectiveness of specific policy interventions.

5. Conclusions

Determinants associated with agricultural Internet of Things (IoT) adoption were examined through an integrated framework combining the Technology Acceptance Model (TAM), the Innovation–Decision Process (IDP), and contextual enablers, including facilitating conditions and governmental support. Empirical validation based on survey data from 250 Thai agricultural stakeholders, analyzed using partial least squares structural equation modeling (PLS-SEM), provides insight into how cognitive, behavioral, and environmental factors are associated with continued use intention for IoT adoption in smart farming contexts. Findings confirm the continued relevance of TAM, with perceived usefulness and attitude toward use emerging as the most influential drivers of behavioral intention. Incorporation of IDP constructs, particularly knowledge and persuasion, extends existing adoption models by highlighting the importance of early-stage cognitive and evaluative processes that precede attitude formation. Facilitating conditions demonstrate a significant role in enabling adoption, emphasizing the importance of infrastructure availability, technical support, and training in resource-constrained environments. In contrast, governmental support does not exhibit a statistically significant direct effect, suggesting a gap between policy-level initiatives and user-perceived or operational support. From a theoretical perspective, a context-sensitive adoption framework is established that integrates cognitive processes, behavioral beliefs, and environmental enablers to enhance explanatory and predictive capabilities beyond traditional TAM-based approaches. From a practical perspective, results indicate that strategies to promote agricultural IoT adoption should prioritize perceived system value, strengthen user knowledge, and improve accessible support mechanisms rather than relying solely on top-down policy interventions. Overall, the findings provide empirical evidence from a developing-country context and offer a validated, yet cautiously interpreted, framework for future research on smart farming and digital agriculture. Addressing the socio-technical complexity of technology adoption contributes to more effective, inclusive, and sustainable digital transformation in the agricultural sector. Future research may extend the proposed framework using longitudinal designs and cross-country validation to enhance generalizability.

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Supplementary Materials

Supplementary Table S1. Measurement items, sources, and outer loadings

Item	Construct	Adapted measurement item	Source	Loading
KN1	Knowledge	I understand the basic functions of IoT systems used in agriculture.	Rogers [39]	0.806
KN2	Knowledge	I am aware of how sensors and connected devices can support farm operations.	Rogers [39]	0.882
KN3	Knowledge	I understand the benefits and limitations of agricultural IoT applications.	Rogers [39]	0.956
KN4	Knowledge	I can explain how IoT data can be used for farm decision-making.	Rogers [39]	0.931
PS1	Persuasion	People in my agricultural network encourage the use of IoT technologies.	Rogers [39]	0.533
PS2	Persuasion	Opinions from peers or communities influence my evaluation of agricultural IoT.	Rogers [39]	0.681
PS3	Persuasion	Agricultural IoT is perceived as relevant to improving farm practices.	Rogers [39]	0.860
PS4	Persuasion	Communication and demonstrations make agricultural IoT more convincing.	Rogers [39]	0.748
PEOU1	Perceived ease of use	Learning to operate agricultural IoT systems is easy for me.	Davis [23]; Venkatesh [43]	0.780
PEOU2	Perceived ease of use	Interacting with agricultural IoT systems is clear and understandable.	Davis [23]; Venkatesh [43]	0.865
PEOU3	Perceived ease of use	I find agricultural IoT systems easy to use in farm-related tasks.	Davis [23]; Venkatesh [43]	0.947
PEOU4	Perceived ease of use	It is easy to become proficient with agricultural IoT systems.	Davis [23]; Venkatesh [43]	0.882
PU1	Perceived usefulness	Using agricultural IoT improves the effectiveness of farm management.	Davis [23]	0.840
PU2	Perceived usefulness	Agricultural IoT helps improve productivity and resource efficiency.	Davis [23]	0.901
PU3	Perceived usefulness	Agricultural IoT supports better monitoring and decision-making.	Davis [23]	0.921

Supplementary Table S1. Measurement items, sources, and outer loadings. (continued)

Item	Construct	Adapted measurement item	Source	Loading
PU4	Perceived usefulness	Overall, agricultural IoT is useful for farming operations.	Davis [23]	0.912
ATT1	Attitude toward use	Using agricultural IoT is a good idea for modern farming.	Davis [23]	0.829
ATT2	Attitude toward use	I have a positive attitude toward the use of agricultural IoT technologies.	Davis [23]	0.902
ATT3	Attitude toward use	Using agricultural IoT is beneficial for agricultural work.	Davis [23]	0.970
ATT4	Attitude toward use	I support the use of IoT technologies in farming.	Davis [23]	0.942
BI1	Continued use intention	I intend to continue using or supporting agricultural IoT technologies.	Venkatesh et al. [43]	0.898
BI2	Continued use intention	I plan to use or promote agricultural IoT in future agricultural activities.	Venkatesh et al. [43]	0.924
BI3	Continued use intention	I expect to remain engaged with agricultural IoT systems.	Venkatesh et al. [43]	0.945
BI4	Continued use intention	I would recommend continued use of agricultural IoT technologies.	Venkatesh et al. [43]	0.918
FC1	Facilitating conditions	Necessary infrastructure is available to support agricultural IoT use.	Venkatesh et al. [43]	0.720
FC2	Facilitating conditions	Technical support is available when using agricultural IoT systems.	Venkatesh et al. [43]	0.801
FC3	Facilitating conditions	Training or guidance is available for agricultural IoT operations.	Venkatesh et al. [43]	0.844
FC4	Facilitating conditions	Resources needed for agricultural IoT use are reasonably accessible.	Venkatesh et al. [43]	0.732
GS1	Governmental support	Government policies support the adoption of agricultural IoT technologies.	Li et al. [41]	0.796
GS2	Governmental support	Government agencies provide useful information about smart farming.	Li et al. [41]	0.887
GS3	Governmental support	Government programs help reduce barriers to agricultural IoT adoption.	Li et al. [41]	0.949
GS4	Governmental support	Public support mechanisms encourage the implementation of agricultural IoT.	Li et al. [41]	0.912

Supplementary Table S2. Effect size (f^2) statistics

This table reports the effect size (f^2) values for all structural relationships in the proposed model. Effect sizes reflect the relative contribution of each exogenous construct to its corresponding endogenous construct. According to Hair et al. [42], f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively.

Exogenous Construct	Endogenous Construct	f^2 Value	Effect Magnitude
PEOU	ATT	0.001	Negligible
PS	ATT	0.077	Small
PU	ATT	0.570	Large
ATT	BI	0.676	Large
FC	BI	0.129	Small–Medium
GS	BI	0.006	Negligible
PS	BI	0.001	Negligible
KN	PEOU	0.885	Large
KN	PS	0.278	Medium
KN	PU	0.027	Small
PEOU	PU	0.385	Large

Note: Interpretation of effect sizes follows Hair et al. (2019): $f^2 \geq 0.02$ (small), ≥ 0.15 (medium), and ≥ 0.35 (large).

Supplementary Table S3. Indirect effects and mediation analysis

This table presents the indirect effects among constructs to examine mediation mechanisms in the proposed model. Indirect effects were estimated using a bootstrapping procedure with 5,000 resamples. Statistical significance of the indirect paths provides evidence for the presence and strength of mediation relationships among cognitive, behavioral, and contextual constructs.

Indirect Path	Indirect Effect (β)	t-value	p-value	Mediation Type	Result	95% CI
KN $\rightarrow$ PEOU $\rightarrow$ PU	0.409	6.85	<0.001	Partial	Significant	[0.292, 0.526]
KN $\rightarrow$ PU $\rightarrow$ ATT	0.108	2.03	0.042	Partial	Significant	[0.004, 0.212]
PU $\rightarrow$ ATT $\rightarrow$ BI	0.441	9.77	<0.001	Partial	Significant	[0.353, 0.529]
PS $\rightarrow$ ATT $\rightarrow$ BI	0.130	2.98	0.003	Full	Significant	[0.044, 0.216]
KN $\rightarrow$ PS $\rightarrow$ ATT	0.095	2.76	0.006	Partial	Significant	[0.028, 0.162]

Note: Indirect effects were evaluated using bootstrapping (5,000 resamples). Significance is determined at $p < 0.05$. Mediation type is classified based on the significance of direct and indirect effects.

Supplementary Table S4. Predictive relevance diagnostics for endogenous constructs.

This table summarizes predictive relevance diagnostics for endogenous constructs based on Q^2 values. These indicators complement the explanatory power (R^2) and predictive relevance results reported in the main text (Tables 9 and 10).

Construct	Q^2 Value	Predictive Strength	Interpretation
BI	0.401	High	Strong predictive relevance
ATT	0.356	High	Strong predictive relevance
PU	0.291	Moderate	Moderate predictive relevance
PEOU	0.243	Moderate	Moderate predictive relevance
PS	0.198	Moderate	Moderate predictive relevance

Note: Q^2 values greater than zero indicate predictive relevance. Values of approximately 0.02, 0.15, and 0.35 suggest small, medium, and large predictive relevance, respectively.