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The Role of Perception as a Mediating Mechanism in Organic Rice Farming Technology Adoption: Evidence from Northeastern Thailand

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Abstract

This study examines the role of Perceived Innovation Characteristics (PIC) as a mediating mechanism linking structural context to Behavioral Intention (BI) in the adoption of drone and microorganism technologies within organic rice farming systems in Northeastern Thailand. Quantitative data were collected from 240 organic rice farmers and analyzed using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). The findings indicate that PIC exerts a significant positive effect on Technology Appraisal (TA) ($\beta = 0.821$) and directly influences Behavioral Intention ($\beta = 0.372$). In contrast, the path from TA to BI was statistically insignificant and removed from the final structural model, suggesting that technology appraisal alone is insufficient to translate into behavioral intention in organic rice farming contexts. Regarding structural determinants, Institutional and Social Support (ISS) significantly influences PIC ($\beta = 0.284$), but does not directly affect BI, while Contextual Capacity (CC) directly influences BI ($\beta = 0.315$) without mediation. Furthermore, Technology Readiness (TR) significantly affects both TA ($\beta = 0.241$) and BI ($\beta = 0.223$), indicating an asymmetric role in the adoption process. The structural model explains a moderate proportion of variance in BI ($R^2 = 0.264$) and a moderate-to-high proportion in TA ($R^2 = 0.579$). These findings suggest that policy interventions should prioritize perception-oriented strategies rather than relying solely on resource provision. Specifically, government and extension agencies should implement demonstration-based learning programs, subsidized pilot trials for drone usage, and community-based knowledge transfer mechanisms to enhance farmers' perception of relative advantage, trialability, and observability. Overall, the results support a perception-mediated adoption model, indicating that technology adoption in organic rice farming is shaped by perception formation under structural and economic constraints.

Keywords: Agricultural Technology Adoption, Perceived Innovation Characteristics, Organic Agriculture, Structural Equation Modeling, Rural Innovation

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Introduction

Over the past decade, global rice production systems have faced intensifying structural pressures across multiple dimensions, including climate variability, rising input costs, and a contraction of the agricultural labor force driven by rural–urban migration and demographic aging. As rice remains a staple food for a large share of the world's population, its production is not merely a sectoral economic activity but a foundational pillar of food security. It reflects a country's capacity to sustain productivity, economic viability, and environmental sustainability simultaneously. Within this context, agricultural adaptation has increasingly shifted toward precision and smart farming systems that integrate digital technologies—such as uncrewed aerial vehicles (UAVs), spatial data systems, and data-driven farm management—with biological innovations, including biofertilizers and microorganisms that enhance soil health. These approaches aim to improve efficiency, reduce chemical dependency, and lower long-term production costs.

In Thailand, rice continues to serve both as a strategic export commodity and as a primary source of rural household income, particularly in Northeastern Thailand, a region of substantial socio-economic importance in agricultural production. However, the medium- to long-term competitiveness of the Thai rice sector is increasingly challenged by rising production costs, yield volatility, and global market pressures emphasizing food safety, sustainability standards, and reduced environmental impact. At the policy level, the structural transition is framed as a shift from labor-intensive and chemical-intensive production systems toward technology- and innovation-based models. Agricultural drones offer potential cost reductions in labor and greater consistency in field operations, such as precision spraying and seeding. Meanwhile, biofertilizers and microbial inputs represent key mechanisms for reducing reliance on synthetic inputs and restoring soil quality over time.

In this context, rice farming—particularly organic rice production—provides a critical empirical setting for examining agricultural technology adoption. Rice is not only Thailand's primary staple crop but also a central component of rural livelihoods, especially in Northeastern Thailand, where smallholder farmers dominate the production structure. Organic rice systems further intensify production constraints, as farmers operate under reduced chemical input regimes, higher labor requirements, and stricter sustainability standards. These conditions amplify the importance of both structural limitations and perceptual evaluation in shaping adoption decisions. Therefore, organic rice farmers represent a theoretically relevant and analytically appropriate group for investigating perception-mediated technology adoption under real-world constraints.

Nevertheless, technological potential does not automatically translate into actual adoption and sustained use—particularly among smallholder farmers operating under constraints of capital, skills, and institutional support. Classical reviews of agricultural innovation adoption consistently highlight structural determinants such as farm size, liquidity, access to credit, and information constraints as defining the feasibility boundaries of adoption decisions. Yet empirical evidence across countries remains heterogeneous, and structural resource variables alone often fail to fully explain adoption behavior. A critical explanatory gap concerns the internal mechanism that transforms contextual constraints into behavioral intention—namely, farmers' processes of perception and appraisal regarding innovation characteristics.

From a theoretical standpoint, Diffusion of Innovations (DOI) theory posits that adoption decisions are shaped by how individuals perceive innovation attributes such as relative advantage, trialability, and observability, which function as interpretive mediators between external information and adoption decisions (Rogers, 2003). Technology Acceptance and Technology Readiness perspectives further emphasize that perception is not merely

attitudinal commentary but a mechanism linking technological conditions and psychological factors to usage intention. In particular, perceived usefulness and perceived ease of use play central roles in technology acceptance (Davis, 1989), while technology readiness captures internal drivers and inhibitors, such as optimism and innovativeness versus insecurity and discomfort (Parasuraman, 2000). Integrated frameworks, such as UTAUT, likewise underscore the roles of performance expectancy, effort expectancy, and facilitating conditions—all of which operate through perceptual dimensions prior to manifesting as behavioral intention.

Against this theoretical background, this article advances a mechanism-based argument: explaining agricultural technology adoption solely through structural determinants risks overlooking the core decision-making process observed in practice. Many contextual constraints influence adoption indirectly through their transformation into perceptions of innovation characteristics, rather than exerting direct effects on behavioral intention. Accordingly, this study conceptualizes *Perceived Innovation Characteristics* (PIC) as a mediating variable that connects structural context and readiness—namely, Contextual Capacity, Institutional and Social Support, Pro-sustainability Orientation, and Technology Readiness—to technology adoption intention.

The central research question is therefore: How do perceived innovation characteristics function as a mediating mechanism between farmers' contextual conditions and their intention to adopt technology? The empirical focus is on the adoption of agricultural drone and microorganism/biofertilizer technologies in organic rice production systems in Northeastern Thailand. The proposed structural model positions contextual and readiness factors as antecedents, conceptualizes PIC as the core transmission mechanism, and links it to both Technology Appraisal (TA) and Behavioral Intention (BI) in a sequential adoption logic.

To address the research question, this study pursues the following objectives:

1. To examine the effects of structural and readiness factors (Contextual Capacity, Institutional and Social Support, Pro-sustainability Orientation, and Technology Readiness) on Perceived Innovation Characteristics (PIC).
2. To analyze the role of PIC as a mediating mechanism linking structural context to Technology Appraisal (TA) and Behavioral Intention (BI).
3. To evaluate the direct and indirect pathways influencing technology adoption in organic rice farming systems.

Finally, this study contributes at two levels. Theoretically, it shifts the explanatory emphasis from structural variables alone to perception-based mechanisms, integrating DOI and readiness/acceptance frameworks within a unified transmission perspective. Practically, it offers an interpretive framework for designing policy and extension measures that prioritize perception formation—such as enhancing observability of outcomes, reducing trial costs, and mitigating psychological resistance—rather than relying solely on information dissemination or broad-based resource support.

Research Objectives

1. To examine the effects of structural and readiness factors (Contextual Capacity, Institutional and Social Support, Pro-sustainability Orientation, and Technology Readiness) on Perceived Innovation Characteristics (PIC).
2. To analyze the role of PIC as a mediating mechanism linking structural context to Technology Appraisal (TA) and Behavioral Intention (BI).
3. To evaluate the direct and indirect pathways influencing technology adoption in organic rice farming systems.

Literature Review

Theoretical Framework and Hypotheses Explaining contemporary agricultural technology adoption cannot be confined to the analysis of individual attitudes or satisfaction alone. Rather, it requires an integrated framework that systematically combines structural factors, institutional conditions, value orientations, and behavioral mechanisms. Recent studies have emphasized that the adoption gap in rural areas of developing countries cannot be adequately explained by perceived usefulness alone; instead, it is closely associated with resource constraints, risk exposure, and market imperfections (Broegaard, Vongvisouk, & Mertz, 2017). Accordingly, this study conceptualizes *Perceived Innovation Characteristics* (PIC) as a mediating mechanism linking structural context and technological readiness to technology appraisal and behavioral intention.

Diffusion of Innovation (DOI): Innovation Attributes and Perception

Rogers' (2003) Diffusion of Innovations (DOI) theory posits that adoption decisions depend on individuals' perceptions of key innovation attributes, including relative advantage, compatibility with existing practices, trialability, observability, and complexity. Importantly, these attributes are not objective properties of a technology per se; rather, they represent users' perceptions that function as interpretive mechanisms transforming external information into adoption decisions.

Empirical research in agricultural contexts consistently supports the role of perceived innovation attributes in shaping adoption behavior. For instance, Liu et al. (2018) demonstrate that the adoption of sustainable agricultural technologies depends more on perceived economic viability and risk-manageability than on the mere availability of the technology itself. Similarly, Broegaard, Vongvisouk, and Mertz (2017) show that households with limited assets may acknowledge positive benefits yet still fail to enter adoption pathways, highlighting that perception constitutes a necessary—but not sufficient—condition, as it must be shaped by structural constraints.

In the present study, the construct *Perceived Innovation Characteristics* (PIC) operationalizes DOI attributes, with particular emphasis on relative advantage, trialability, observability, and ease of use (Rogers, 2003). PIC is therefore positioned as a mediating variable linking contextual determinants to technology appraisal.

Technology Readiness: Psychological Predisposition Toward Technology

While DOI explains how innovation attributes are perceived, technology adoption also depends on users' psychological readiness. The Technology Readiness Index (TRI) proposed by Parasuraman (2000) suggests that individuals possess both enabling (optimism and innovativeness) and inhibiting (discomfort and insecurity) dimensions that shape their predisposition toward technology adoption.

Subsequent research confirms that these readiness components influence perceived usefulness and perceived ease of use (Liljander, Gillberg, Gummerus, & van Riel, 2006), aligning with the Technology Acceptance Model (TAM), which identifies perceived usefulness and perceived ease of use as key determinants of behavioral intention (Davis, 1989; Venkatesh & Davis, 2000).

In the context of organic agriculture, drone technologies and bio-microbial inputs differ in complexity and perceived risk. Psychological readiness thus plays a critical role in transforming technical feasibility into behavioral willingness. In this study, *Technology Readiness* (TR) is conceptualized as an antecedent influencing both Perceived Innovation Characteristics (PIC) and Technology Appraisal (TA). Although drone technologies and bio-microbial inputs differ substantially in their technical nature—mechanical and digital versus biological and ecological—both can be evaluated through a common perceptual framework

based on DOI attributes. Farmers assess these technologies in terms of relative advantage (e.g., cost reduction or yield improvement), trialability (ease of experimentation), observability (visibility of outcomes), and compatibility with existing practices. Therefore, despite their heterogeneity, both technologies are analytically unified under the construct of Perceived Innovation Characteristics (PIC), which captures the perceptual mechanisms underlying adoption decisions.

Structural Context and Agricultural Innovation Systems

Technology adoption in rural settings does not occur in isolation; it unfolds within constraints shaped by capital markets, labor availability, and institutional structures. Feder et al. (1985) highlight the roles of farm size and access to credit in technology adoption. Abdulai and Huffman (2014) demonstrate that adoption decisions are made under risk and imperfect market conditions. Khonje et al. (2018) further show that access to community networks and social capital influences the intensity of soil conservation technology use.

The Agricultural Innovation Systems (AIS) framework emphasizes the roles of networks, extension services, and innovation intermediaries in reducing transaction costs and uncertainty (Eastwood et al., 2017). Accordingly, *Contextual Capacity* (CC) in this study reflects household resource endowments (land, labor, income, credit access), while *Institutional and Social Support* (ISS) captures institutional mechanisms and network-based learning processes that facilitate risk reduction and knowledge diffusion.

Synthesis of the Conceptual Framework and Structural Model

Integrating DOI, TAM, TRI, and AIS, this study proposes a causal pathway linking antecedent conditions (Contextual Capacity [CC], Institutional and Social Support [ISS], Pro-sustainability Orientation [PSO], and Technology Readiness [TR]) to Perceived Innovation Characteristics (PIC), which subsequently influence Technology Appraisal (TA) and Behavioral Intention (BI).

The principal structural pathway of the model is conceptualized as:

CC / ISS / PSO / TR → PIC → TA → BI

Within this framework, PIC and TA function as sequential mediators in the technology adoption decision process.

Organic Farming Specificity and Perception under Constraint

Technology adoption in organic farming systems differs fundamentally from conventional agriculture due to distinct production constraints and risk structures. Organic farmers operate under limited use of synthetic inputs, stricter certification requirements, and higher dependence on ecological processes, which increase both yield uncertainty and labor intensity. As a result, their decision-making context is characterized by heightened sensitivity to risk, longer return horizons, and greater reliance on experiential validation.

In such contexts, the evaluation of new technologies is less likely to be driven solely by objective performance metrics and more strongly shaped by perceived compatibility with organic practices, perceived risk reduction, and observable outcomes under real conditions. This implies that perception plays a more central role as a filtering and interpretive mechanism compared to conventional systems. Consequently, pro-sustainability orientation (PSO) may not uniformly translate into adoption behavior, as farmers may prioritize risk mitigation over normative environmental preferences when faced with uncertain outcomes. This reinforces the need to conceptualize perception as a mediating mechanism within constrained agricultural systems.

Conceptual Framework

The conceptual framework integrates contextual, institutional, and behavioral factors associated with agricultural technology adoption in organic rice production systems. Figure 1 illustrates the proposed relationships among the key constructs examined in this study.

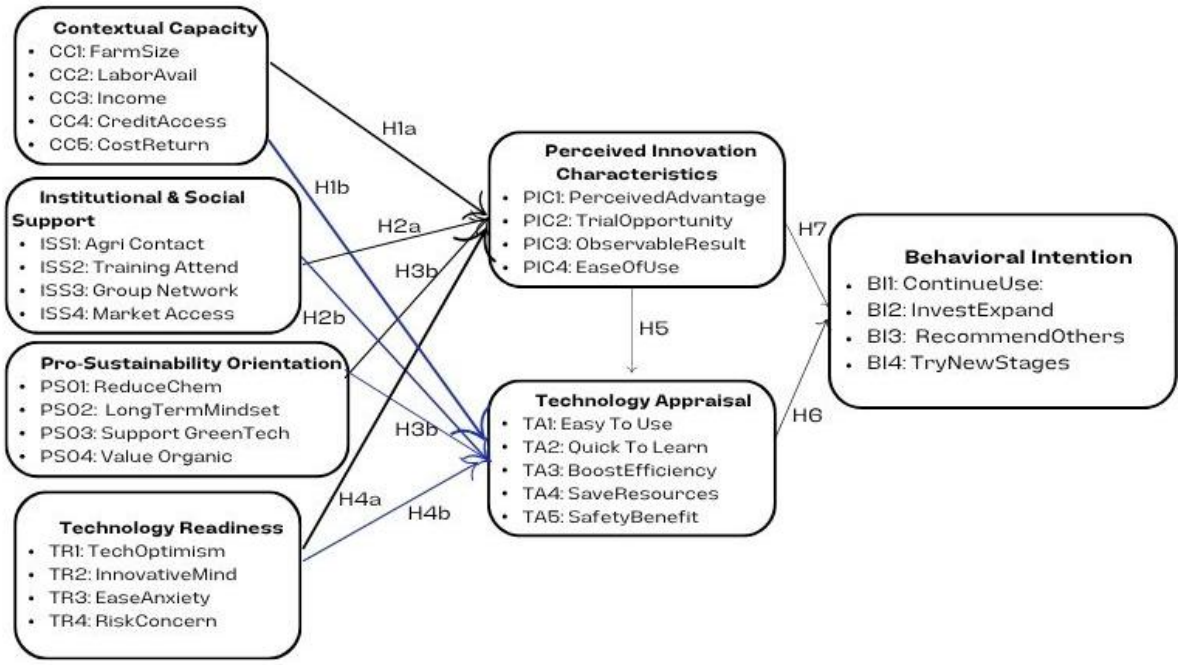


Figure 1: Conceptual Framework of Agricultural Technology Adoption in Organic Rice Production Systems

Based on this framework, the proposed relationships among the constructs are further elaborated through the research hypotheses presented in the following section.

Research Hypotheses

Based on the integrated theoretical framework outlined above, the following hypotheses are proposed.

Table 1 Research Hypotheses and Theoretical Foundations

Code	Hypothesis Statement	Supporting Theories / References
H1a	Contextual Capacity (CC) has a positive effect on Perceived Innovation Characteristics (PIC).	Liu et al. (2018) – resource constraints affect perception and adoption pathways
H1b	Contextual Capacity (CC) has a positive effect on Technology Appraisal (TA).	Abdulai & Huffman (2014) – investment decisions under risk and capital constraints

Code	Hypothesis Statement	Supporting Theories / References
H1c	Contextual Capacity (CC) has a positive effect on Behavioral Intention (BI).	Atieno et al. (2020) – farm size and credit access influence adoption decisions
H2a	Institutional and Social Support (ISS) has a positive effect on Perceived Innovation Characteristics (PIC).	Eastwood et al. (2017) – innovation intermediaries shape farmers' perceptions
H2b	Institutional and Social Support (ISS) has a positive effect on Technology Appraisal (TA).	Pigford, Hickey, & Klerkx (2018) – institutional support reduces uncertainty and enhances evaluation
H2c	Institutional and Social Support (ISS) has a positive effect on Behavioral Intention (BI).	Barnes et al. (2019) – Agricultural Innovation Systems and institutional linkages
H3a	Pro-sustainability Orientation (PSO) has a positive effect on Perceived Innovation Characteristics (PIC).	Dunlap et al. (2000) – New Environmental Paradigm; Stern (2000) – Value-Belief-Norm theory
H3b	Pro-sustainability Orientation (PSO) has a positive effect on Technology Appraisal (TA).	Stern (2000) – environmental values influence behavioral evaluation
H3c	Pro-sustainability Orientation (PSO) has a positive effect on Behavioral Intention (BI).	Ajzen (1991); Stern (2000) – values shape behavioral intention
H4a	Technology Readiness (TR) has a positive effect on Perceived Innovation Characteristics (PIC).	Parasuraman (2000) – TRI; Liljander et al. (2006) – readiness affects perception
H4b	Technology Readiness (TR) has a positive effect on Technology Appraisal (TA).	Parasuraman (2000); Venkatesh & Davis (2000)
H4c	Technology Readiness (TR) has a positive effect on Behavioral Intention (BI).	Venkatesh et al. (2003) – UTAUT; Parasuraman (2000)
H5	Perceived Innovation Characteristics (PIC) has a positive effect on Technology Appraisal (TA).	Rogers (2003); Davis (1989)

Code	Hypothesis Statement	Supporting Theories / References
H6	Technology Appraisal (TA) has a positive effect on Behavioral Intention (BI).	Rejeb et al. (2022)
H7	Perceived Innovation Characteristics (PIC) has a positive effect on Behavioral Intention (BI).	Venkatesh et al. (2003)

The proposed structural model reflects a sequential process of **"context → readiness → perception → appraisal → intention."** This framework aligns with behavioral economic logic, suggesting that smallholder farmers' investment decisions are made under conditions of constraint and uncertainty, rather than being driven solely by stable preferences or attitudinal inclination. Technology adoption in this context is therefore conceptualized as a constrained optimization process shaped by structural endowments, institutional support, psychological readiness, and perception-based evaluation mechanisms.

Research Methodology

Research Design and Sample

The quantitative phase of this study was conducted in Northeastern Thailand within the operational context of the Save Planet Rice Platform, which is aligned with the Bio–Circular–Green (BCG) economic model. The study covered 16 sub-districts across 5 districts in 5 provinces (Roi Et, Maha Sarakham, Buriram, Sisaket, and Ubon Ratchathani). These areas were selected due to their relatively well-defined networks of organic rice farmers, established aggregation and processing mechanisms, and formal market linkages with local governmental agencies. Such a setting provides an appropriate empirical context for examining the structural–institutional–technological readiness–value appraisal–intention mechanisms underlying technology adoption.

The target population consisted of registered organic rice farmers participating in the platform's activities. The total population consisted of 2,230 registered organic rice farmers across 16 sub-districts in five provinces participating in the Save Planet Rice Platform under the Bio-Circular-Green (BCG) economy model (Save Planet Rice Project, 2023).

The sample size was determined using the RMSEA-based approach proposed by MacCallum, Browne, and Sugawara (1996), which is appropriate for covariance-based SEM. Given $\alpha = 0.05$, statistical power = 0.80, $RMSEA_0 = 0.05$, RMSEA_A = 0.08, and model degrees of freedom ($df \approx 525$), the required sample size was approximately $N \approx 236$. Therefore, a final sample size of 240 respondents was used to ensure adequate statistical power while allowing for minor data loss. This range is consistent with prior SEM studies suggesting that sample sizes between 200–300 are sufficient for models with moderate complexity and adequate factor loadings (Kline, 2016).

Measurement

The study employs seven latent constructs measured using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The indicators were coded according to the standardized variable scheme of the research project, as summarized below:

Table 2 Latent Constructs, Observed Indicators, and Their Roles in the Structural Model

Latent Variable	Indicators (Observed Codes)	Role in the Model
Contextual Capacity (CC)	CC1–CC5	Independent variable
Institutional & Social Support (ISS)	ISS1–ISS4	Independent variable
Pro-Sustainability Orientation (PSO)	PSO1–PSO4	Independent variable
Technology Readiness (TR)	TR1–TR4	Independent variable
Perceived Innovation Characteristics (PIC)	PIC1–PIC4	Mediator
Technology Appraisal (TA)	TA1–TA5	Mediator
Behavioral Intention (BI)	BI1–BI4	Endogenous variable

Instrument development followed established procedures to ensure:

1) Content validity was assessed by three subject-matter experts using the Index of Item-Objective Congruence (IOC), with item-level scores ranging from 0.67 to 1.00, exceeding the commonly accepted threshold of 0.50.Internal consistency reliability, assessed via Cronbach's alpha (Cronbach, 1951)

2) Internal consistency reliability was confirmed with Cronbach's alpha coefficients ranging from 0.78 to 0.91 across all constructs, exceeding the recommended threshold of 0.70. Composite Reliability (CR) values ranged from 0.80 to 0.93, indicating satisfactory construct reliability.

3) **Construct validity**, examined through Confirmatory Factor Analysis (CFA) to verify that observed indicators adequately reflect their respective latent constructs prior to structural estimation.

To control for response direction effects, negatively worded items (e.g., those reflecting concern or insecurity) were reverse-coded according to the project's coding manual prior to conducting CFA and SEM analyses.

Data Analysis

Data analysis was conducted using a Covariance-Based Structural Equation Modeling (CB-SEM) approach. The analytical procedure followed three logically connected stages:

(1) Measurement Model Assessment (CFA)

The validity and reliability of the latent constructs were evaluated using CFA. The following indicators were reported:

1) Standardized factor loadings
2) Composite Reliability (CR)
3) Average Variance Extracted (AVE)
4) Discriminant validity (e.g., HTMT ratio or other appropriate criteria consistent with the analytical framework adopted)

(2) Structural Model Estimation and Hypothesis Testing

The structural model specified causal paths from **CC / ISS / PSO / TR → PIC → TA → BI**, consistent with the proposed sequential mediation framework.

Direct and indirect effects were tested, and standardized path coefficients (β), p-values, and effect magnitudes were reported to enable mechanism-based interpretation.

(3) Mediation Testing and Model Fit Evaluation

Mediation effects were assessed through statistically supported indirect effect testing. In SEM practice, bootstrap confidence intervals are commonly recommended when data conditions permit.

Model fit was evaluated using a set of complementary indices, including: χ^2/df, CFI, TLI, RMSEA, SRMR

Model adequacy was interpreted holistically rather than relying on a single cutoff criterion. As emphasized in SEM literature, cutoff values should be applied pragmatically, taking into account model complexity and field-data conditions (Hu & Bentler, 1999).

To mitigate the risk of **Common Method Bias (CMB)** arising from single-source self-reported data, both procedural and statistical remedies were implemented. Procedural controls included respondent anonymity, neutral wording, and careful question sequencing to reduce priming effects. Preliminary statistical checks consistent with applied social science research practices (e.g., Harman's single-factor logic) were conducted prior to structural interpretation.

Results

Respondent Profile and Technology Exposure

Table 3 Key Descriptive Characteristics of Respondents (N = 240)

Indicator	Value
Farmers aged 50 years or above	66.6%
Married / living together	82.9%
Primary education	79.2%
Average total landholding	18.7 rai
Average organic rice area	6.3 rai
Own land only	65.8%
Households with secondary occupation	59.2%
Ever contacted extension officers in past 12 months	59.2%
Ever attended training/study visit in past 12 months	43.3%
Ever participated in government support programs	53.3%
Never used drones in past 12 months	70.0%
Ever trained in drone use	32.5%
Ever trained in microorganism use	61.7%
Current regular use of microorganisms	15.9%

The sample reflects a predominantly older smallholder farming population with limited household labor, low formal education, and moderate institutional exposure. Technology experience also differs across the two focal innovations: drone use remains limited and is concentrated in trial or service-based access, whereas microorganism-related practices show broader training exposure and more gradual integration into production routines. These descriptive patterns provide important context for the subsequent SEM analysis, particularly in interpreting why perception may operate as a key mechanism linking structural conditions to behavioral intention.

Factor Loadings

In this study, only standardized factor loadings (λ) equal to or greater than 0.50 are reported to reflect the strength of the relationship between observed indicators and their respective latent constructs. This reporting threshold is consistent with common practice in CFA and SEM applications (Kline, 2016; Hair et al., 2019).

Table 4 Standardized Factor Loadings Meeting the Acceptance Criterion (λ ≥ 0.50)

Latent Variable	Indicator	Standardized Loading (λ)	Criterion Met
ContextualCapacity (CC)	CC1	0.838	✓
	CC2	0.833	✓
	CC3	0.802	✓
	CC4	0.764	✓
	CC5	0.785	✓
Institutional & Social Support (ISS)	ISS1	0.718	✓
	ISS2	0.705	✓
	ISS3	0.925	✓
	ISS4	0.882	✓
Pro-Sustainability Orientation (PSO)	PSO1	0.892	✓
	PSO2	0.925	✓
	PSO3	0.906	✓
	PSO4	0.939	✓
Technology Readiness (TR)	TR1	0.913	✓
	TR2	0.807	✓
	TR3	0.553	✓
	TR4	0.637	✓
Perceived Innovation Characteristics (PIC)	PIC2	0.779	✓
	PIC3	0.701	✓
Technology Appraisal (TA)	TA1	0.673	✓
	TA2	0.717	✓
	TA3	0.713	✓
	TA4	0.547	✓
	TA5	0.510	✓
Behavioral Intention (BI)	BI1	0.772	✓
	BI2	**0.909**	✓
	BI3	0.709	✓
	BI4	0.579	✓

Indicators with standardized loadings below 0.50 (e.g., PIC1 = 0.416 and PIC4 = 0.387) are not reported in this table in accordance with the study's reporting criterion of presenting only loadings that meet the threshold.

If such indicators were retained in the revised model, theoretical or contextual justifications should be clearly articulated, and the issue should be acknowledged as a measurement limitation in the limitations section of the article (Kline, 2016; Hair et al., 2019).

Construct Reliability, Convergent Validity, and Discriminant Validity

Convergent Validity and Composite Reliability

Convergent validity was assessed using the conventional criteria of **Average Variance Extracted (AVE) ≥ 0.50** and **Composite Reliability (CR) ≥ 0.70**. In cases where AVE falls below 0.50 but CR remains acceptable, the construct may still be considered methodologically adequate, provided that theoretical coherence and measurement justification are clearly articulated (Fornell & Larcker, 1981; Hair et al., 2019).

Table 5 Summary of AVE and CR for Latent Constructs (Revised Measurement Model)

Latent Variable	AVE	CR	Methodological Interpretation
Contextual Capacity (CC)	0.650	0.903	Meets criteria → strong convergent validity
Institutional & Social Support (ISS)	0.669	0.889	Meets criteria → strong convergent validity
Pro-Sustainability Orientation (PSO)	0.839	0.954	Very high → clear structural convergence
Technology Readiness (TR)	0.541	0.819	Meets criteria → acceptable level
Perceived Innovation Characteristics (PIC)	0.440	0.658	AVE < .50 and CR < .70 → measurement weakness (requires discussion)
Technology Appraisal (TA)	0.466	0.805	AVE slightly below .50 but CR acceptable → methodologically tolerable under Fornell–Larcker logic
Behavioral Intention (BI)	0.608	0.856	Meets criteria → strong convergent validity

Discriminant Validity (Fornell–Larcker Criterion)

Discriminant validity was evaluated using the Fornell–Larcker criterion, which requires that the square root of AVE (diagonal elements) exceed inter-construct correlations to confirm conceptual distinctiveness (Fornell & Larcker, 1981).

Table 6 Discriminant Validity Based on Fornell–Larcker Criterion

Construct	CC	ISS	PSO	TR	PIC	TA	BI
CC	**0.806**						
ISS	0.733	**0.818**					
PSO	0.558	0.275	**0.916**				
TR	0.685	0.475	0.729	**0.736**			
PIC	0.542	0.276	0.233	0.297	**0.583**		
TA	0.381	0.296	0.247	0.377	0.539	**0.683**	
BI	0.372	0.395	0.094	0.262	0.275	0.278	**0.780**

For all constructs, the square root of AVE exceeds the corresponding inter-construct correlations, supporting acceptable discriminant validity of the measurement model, even after model modification based on modification indices (Fornell & Larcker, 1981; Hair et al., 2019).

Model Fit (Before and After Model Modification)

Model fit evaluation should be interpreted multidimensionally, considering absolute, incremental, residual-based, and parsimony indices. Each category captures different aspects of model

adequacy and exhibits varying sensitivity to sample size and model complexity (Bollen, 1989; Hu & Bentler, 1999; Kline, 2016).

Table 7 Comparison of Model Fit Indices (Before and After Modification)

Fit Index	Practical Threshold	Before Modification	After Modification	Interpretation
χ^2/df	< 3 (or < 5 for field data)	4.48	4.450	Acceptable under field-data tolerance
RMSEA	< .08 (strict) / < .10 (lenient)	0.12	0.082	Substantial improvement; within lenient threshold
CFI	≥ .90	0.855	0.904	Meets minimum criterion after revision
NFI	≥ .90	0.808	0.908	Meets minimum criterion after revision
GFI	≥ .90	0.795	0.887	Slightly below recommended threshold
RMR	< .05	0.044	0.021	Clearly acceptable
TLI/NNFI	≥ .90	0.753	0.912	Meets minimum criterion after revision

Following model modification, RMSEA decreased substantially (≈ 0.12 → 0.082), indicating meaningful practical improvement. Incremental fit indices (CFI, NFI, and TLI) improved beyond minimum acceptable thresholds, suggesting that the revised model achieves sufficient methodological adequacy for mechanism-based interpretation in complex field settings characterized by behavioral and contextual heterogeneity (Hu & Bentler, 1999; Kline, 2016).

Structural Model Results

Hypothesis Testing of the SEM Model (Direct Effects) After Model Modification

Following theory-driven model trimming, statistically insignificant paths were removed to enhance parsimony and reduce estimation instability in the SEM framework. The structural results are summarized in Table **7** and Figure 1.

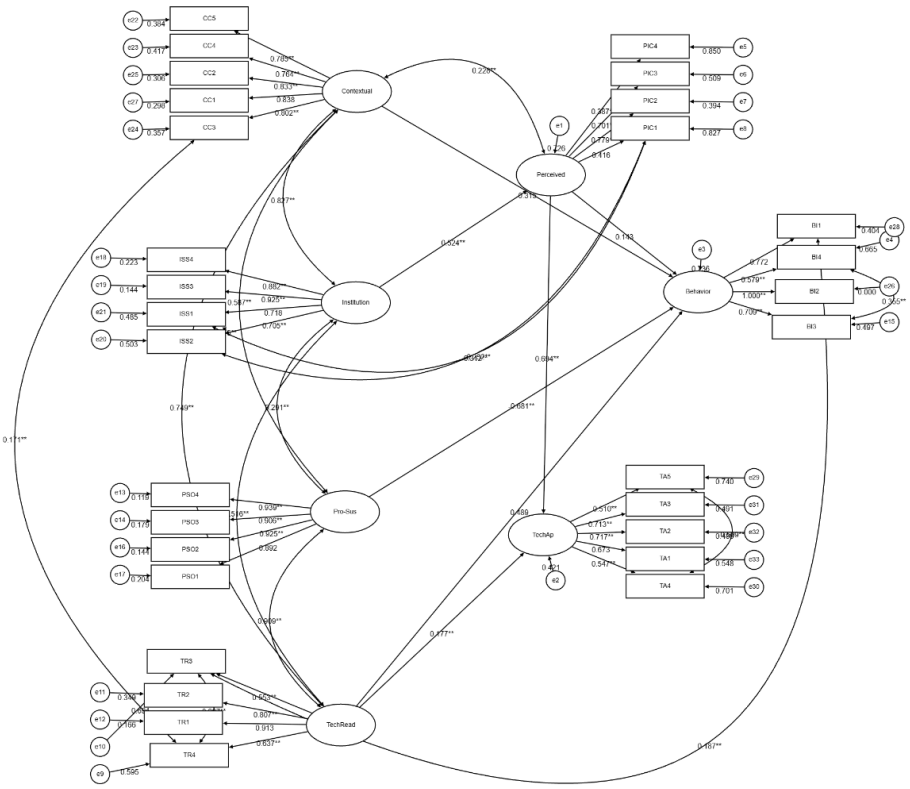


Figure 1 Final SEM with Standardized Estimates

Table 8 Structural Model Results: Direct Effects and Hypothesis Testing

Hypothesis	Structural Path	Unstandardized Estimate	S.E.	C.R. (z)	p-value	Standardized β	Result
H1c	CC → BI	0.279	0.176	1.582	.014	0.315	Supported
H2a	ISS → PIC	0.213	0.086	2.472	.013	0.284	Supported
H3c	PSO → BI	–0.194	0.090	–2.158	.031	–0.206	Supported (Negative)
H4b	TR → TA	0.228	0.095	2.400	.016	0.241	Supported
H4c	TR → BI	0.201	0.093	2.161	.031	0.223	Supported
H5	PIC → TA	1.353	0.156	8.673	< .001	0.821	Supported
H7	PIC → BI	0.358	0.121	2.959	.003	0.372	Supported

Interpretation of Direct Effects

1) **CC → BI is significant**, whereas CC → PIC and CC → TA are not. This suggests that structural resource capacity functions as a *direct structural driver* of behavioral intention, rather than operating through perception-based technological evaluation processes.

2) **ISS → PIC is significant**, but ISS → TA and ISS → BI are not. This indicates that Institutional and Social Support primarily functions as a *perception-formation mechanism*, reducing information asymmetry and enabling farmers to recognize innovation attributes before formal evaluation occurs.

3) **TR → TA and TR → BI are both significant**, demonstrating that Technology Readiness plays a dual role: influencing rational technological evaluation and directly reinforcing behavioral intention.

4) **PSO → BI exhibits a significant negative effect**, contrary to the hypothesized direction. This finding reflects a behavioral tension between sustainability-oriented values and actual investment decisions under uncertainty in organic farming systems, where financial return horizons and outcome variability remain critical considerations.

5) The structural core of the model lies in the significant paths **PIC → TA** and **PIC → BI**, whereas **TA → BI is not significant**. This suggests that technology appraisal alone is insufficient to translate into behavioral intention unless supported by perception-based mechanisms and enabling contextual conditions.

The Role of Perception as a Transmission Mechanism (Mediation Analysis)

In SEM-based mediation analysis, both direct and indirect effects must be considered, particularly when evaluating indirect effects using resampling or bootstrapping approaches (Preacher & Hayes, 2008).

In the final structural model, however, the path **TA → BI (H6)** was statistically insignificant and therefore removed. Consequently, the sequential mediation pathway **PIC → TA → BI** is not supported in the final structural configuration. In other words, PIC functions clearly as a transmission mechanism, but TA does not operate as a bridge toward behavioral intention under the revised model.

Table 9 Direct and Indirect Effects Retained After Model Modification

Determinant (X)	Mediator	Outcome (Y)	Path	Direct Effect	Indirect Effect (Unstandardized)	Mechanism Interpretation
ISS	PIC	TA	ISS → PIC → TA	(ISS→TA removed)	0.213 × 1.353 = 0.288	ISS enhances TA via perception formation
ISS	PIC	BI	ISS → PIC → BI	(ISS→BI removed)	0.213 × 0.358 = 0.076	ISS influences BI indirectly through PIC
PIC	TA	BI	PIC → TA → BI	(TA→BI removed)	Not supported	Technology appraisal does not translate into BI

Mechanism-Based Interpretation

1) The findings clearly support a **perception-mediated mechanism**, particularly in the case of ISS. Institutional and social support operate primarily by shaping perception—enhancing awareness of relative advantage, compatibility, trialability, and observability—before influencing TA and BI.

2) In contrast, CC demonstrates a **direct-to-intention pathway (CC → BI)**, reflecting field-based realities where adoption behavior is strongly constrained by resource capacity and practical feasibility.

3) Most critically, the absence of a significant **TA → BI** path indicates that perceived usefulness or ease of use alone does not automatically elevate evaluation into behavioral intention. This suggests the presence of additional economic frictions, risk considerations, or contextual constraints not fully captured within the model. Such findings are consistent with applied SEM research in complex behavioral settings, where decision-making is not driven by purely rational appraisal processes (Bollen, 1989; Kline, 2016).

Table 10 Explained Variance of Endogenous Constructs

Endogenous Construct	R^2	Methodological Assessment
Perceived Innovation Characteristics (PIC)	0.274	Moderate explanatory power
Technology Appraisal (TA)	0.579	Moderate to relatively high explanatory power
Behavioral Intention (BI)	0.264	Moderate explanatory power

The model explains a moderate proportion of variance in Behavioral Intention ($R^2 = 0.264$), reflecting the inherent complexity of technology adoption behavior in organic agricultural systems. Adoption decisions remain influenced by factors beyond the structural scope of the model, including market risk, financial conditions, service accessibility, accumulated experiential learning, and operational cost structures. Despite these contextual complexities, the revised structural model demonstrates improved stability and sufficient explanatory adequacy for mechanism-based interpretation.

Discussion

The findings of this study indicate that the adoption of drone and microorganism technologies in organic rice systems is not a linear process in which structural factors directly drive behavior. Rather, it represents a **multi-stage appraisal process under constraints**, consistent with agricultural technology adoption research suggesting that farmers' decisions result from the combined influence of perceptual evaluation, risk management, and resource conditions (Marra, Pannell, & Abadi Ghadim, 2003).

Perceived Innovation Characteristics as the Central Mechanism of Adoption

A key contribution of this study is the identification of **Perceived Innovation Characteristics (PIC)** as a mechanism-based mediator linking Institutional and Social Support (ISS) to Behavioral Intention (BI).

This reflects Diffusion of Innovations theory, which emphasizes perceived relative advantage, trialability, and observability as primary determinants of adoption rates. In agricultural contexts, Rejeb et al. (2022) argue that farmers adopt technologies based on "perceived tangible returns" rather than policy information alone.

Within digital agriculture, Eastwood et al. (2017) demonstrate that institutional network support influences adoption indirectly by shaping farmers' understanding and interpretation of emerging technologies rather than directly determining usage. This indicates that under resource constraints the pathway **ISS → PIC → BI** observed in this study.

In other words, ISS functions to **reduce informational uncertainty**, creating cognitive space for value-based evaluation before farmers form behavioral intentions.

Resource Context as a Structural Driver Beyond Perception Channels

The findings reveal that **Contextual Capacity (CC)** affects Behavioral Intention directly, rather than through perception or appraisal pathways.

This outcome is consistent with classical agricultural economics literature, which identifies farm size, financial liquidity, and labor management capacity as direct determinants of technology adoption, particularly for capital-intensive innovations (Feder et al., 1985).

Marra et al. (2003) further argue that under return uncertainty, farmers evaluate economic risk alongside resource constraints. Thus, even when perceived innovation attributes are positive, low CC may prevent behavioral conversion.

The present results therefore reflect a **decision-under-resource-constraint logic**, supported by empirical findings from Liu, Bruins, and Heberling (2018), who found that resource capacity exerts stronger influence than perception alone in conservation technology adoption in China.

This interpretation is also consistent with the demographic profile of the sample, which is characterized by an aging farming population, limited household labor, and relatively low formal education. These conditions increase the importance of practical feasibility and reduce the likelihood that positive perception or evaluation alone will translate into adoption behavior.

Technology Readiness: Asymmetric Effects and Dual Roles

In this study, **Technology Readiness (TR)** significantly influences both Technology Appraisal (TA) and Behavioral Intention (BI), but not Perceived Innovation Characteristics directly.

This suggests that attitudinal readiness and technological confidence operate primarily at the stages of evaluation and decision-making rather than at the initial perception of innovation attributes.

In digital agriculture contexts, Eastwood et al. (2017) emphasize that farmers' ability to interpret data and manage technological complexity significantly influences adoption decisions, particularly for advanced technologies such as drones and precision systems.

Similarly, Barnes et al. (2019) report that precision agriculture adoption in Europe depends heavily on farmers' technological confidence and skills, which act as accelerators of decision-making rather than primary determinants of initial perception.

Thus, TR operates through two pathways:

(1) Enhancing evaluative capacity

(2) Reducing hesitation in decision-making

Adoption in Organic Farming Systems: A Multi-Stage Process with Structural Bottlenecks

The absence of a significant **TA → BI** pathway in the final model indicates that positive technological appraisal alone is insufficient to elevate evaluation into behavioral intention.

Läpple and Van Rensburg (2011), in studying transitions toward organic farming, demonstrate that adoption of new systems is constrained by market risk, production uncertainty, and institutional barriers, even when farmers hold favorable evaluations.

Moreover, Baumgart-Getz, Prokopy, and Floress (2012), synthesizing multiple studies on conservation practice adoption, conclude that agricultural adoption is a multi-stage process shaped by social, economic, and institutional forces—not merely technical perception or attitude.

Accordingly, adoption of drone and microorganism technologies in organic rice systems should be conceptualized as a **multi-stage appraisal process with structural bottlenecks**, particularly in contexts characterized by organic market risk and income volatility.

A particularly notable finding is the negative relationship between Pro-Sustainability Orientation (PSO) and Behavioral Intention (BI). Rather than indicating a contradiction, this result reflects a tension between sustainability values and economic feasibility under conditions of uncertainty. In organic farming systems, farmers who strongly prioritize sustainability may also be more cautious in adopting new technologies that are perceived as capital-intensive, externally dependent, or potentially misaligned with organic principles. This is especially relevant in the case of drone technologies, which require financial investment or service costs, and may not always produce immediate or observable returns.

From a behavioral perspective, this finding is consistent with risk-averse decision-making under uncertainty, where farmers with strong normative commitments to sustainability prioritize stability and ecological consistency over technological experimentation. Thus, higher PSO may not directly translate into higher adoption intention, particularly when perceived economic risk or compatibility concerns remain unresolved.

Another critical finding is the absence of a significant relationship between Technology Appraisal (TA) and Behavioral Intention (BI). This suggests that positive evaluation of a technology in terms of usefulness, ease of use, or safety is not sufficient to trigger actual intention to adopt.

In the socio-economic context of smallholder organic farming, decision-making is not driven solely by rational evaluation, but is also shaped by resource constraints, labor availability, and accumulated experiential knowledge. Farmers may recognize that a technology is beneficial, yet still refrain from adoption due to financial limitations, uncertainty about returns, or lack of continuous access.

In addition, organic farming systems often involve tacit knowledge, ecological balance, and experiential learning processes that are not fully captured by standard appraisal constructs. As a result, technology appraisal does not automatically convert into behavioral intention unless supported by enabling structural conditions and perceived feasibility in real farm operations.

Although this study focuses on organic rice farming in Northeastern Thailand, the underlying mechanism identified in this study—where structural conditions shape perception, which in turn influences adoption intention—may be applicable to other agricultural systems facing similar constraints. In particular, smallholder production systems characterized by labor limitations, financial constraints, and uncertainty in returns may exhibit similar perception-mediated adoption patterns. However, such generalization should be interpreted cautiously, as differences in crop systems, market structures, and institutional environments may alter the relative importance of each mechanism

Theoretical Implications

Extending the Diffusion of Innovation Framework with Structural Context

The findings clearly demonstrate that **Perceived Innovation Characteristics (PIC)** do not emerge independently of structural conditions. Rather, they are shaped by upstream structural contexts, namely **Contextual Capacity (CC)** at the household level and **Institutional & Social Support (ISS)**, which function as foundational conditions of the technological appraisal process.

The Diffusion of Innovation (DOI) framework (Rogers, 2003) conceptualizes adoption primarily through perceived innovation attributes such as relative advantage, trialability, and observability. However, DOI traditionally emphasizes the individual level and does not systematically elaborate how structural factors influence the *formation of perception*. The present study proposes that perception should not be treated as an independent variable, but rather as a **process-generated outcome shaped by resource and institutional contexts**.

This perspective aligns with Barnes et al. (2019), who found that precision agriculture adoption in Europe depends not only on perceived technological benefits but also on farm-level resource endowments and policy environments. In the context of Thai organic farming, the present findings similarly confirm that perceived benefits of drones and microorganisms are constructed under financial, labor, and network constraints.

Accordingly, this study contributes theoretically by **extending DOI with a structural-context dimension**, proposing that rural innovation diffusion should be conceptualized as a hierarchical process:

Structure → Perception → Appraisal → Intention

Compared with conventional adoption models such as TAM and UTAUT, which emphasize perceived usefulness and ease of use as direct predictors of intention, the findings of this study suggest that such relationships may weaken in contexts characterized by structural constraints and production uncertainty. In organic farming systems, perception alone does not guarantee adoption; instead, it must be supported by resource feasibility and institutional conditions. This highlights the importance of integrating DOI with structural and behavioral perspectives when analyzing technology adoption in real-world agricultural settings.

Proposing a Mediation-Based Adoption Model

The structural analysis confirms the mediating roles of **Perceived Innovation Characteristics (PIC)** and **Technology Appraisal (TA)** between upstream determinants (CC, ISS, PSO, TR) and **Behavioral Intention (BI)**. Certain contextual variables do not exert direct effects on BI but instead operate through technological appraisal mechanisms.

This finding carries important theoretical implications. Much of the technology adoption literature reports linear relationships between readiness/resources and adoption outcomes (Parasuraman, 2000; Venkatesh et al., 2003). In contrast, the present study demonstrates that **Technology Readiness (TR)** influences BI primarily through evaluative mechanisms rather than exclusively through direct pathways.

This pattern is consistent with Iancu & Iancu (2020), who found that farmers adopt digital technologies based on economic value appraisal and risk assessment rather than purely technical motivation. Similarly, Barnes et al. (2019) identify perceived benefits as a bridging mechanism between farm structure and technology implementation.

The study therefore proposes a **mediation-based adoption model**, emphasizing that upstream determinants must be translated through perception and appraisal mechanisms before forming behavioral intention. Such a framework is particularly appropriate for organic farming systems characterized by multi-dimensional constraints.

Integrating Behavioral Economics with Rural Innovation

The results also reflect a logic of **decision-making under constraints**, consistent with behavioral economics perspectives, particularly bounded rationality (Simon, 1955) and decision-making under risk (Kahneman & Tversky, 1979).

Farmers do not decide based on complete information or purely technical calculations. Instead, they engage in subjective evaluation processes involving risk perception, uncertainty management, and trial feasibility. This implies that technology adoption in organic farming systems is fundamentally a **behavioral phenomenon rather than merely a technical one**.

The present study, therefore, contributes to bridging DOI theory with behavioral economics by proposing that rural innovation analysis must integrate perception, risk, and value-appraisal processes. Adoption should be understood as a constrained behavioral evaluation process embedded within structural realities.

Conclusion and Recommendations

Conclusion and Implications

This study demonstrates that the adoption of drone and microorganism technologies in organic rice systems is best understood as a mechanism-based process rather than a direct outcome of structural resources or technological readiness alone. The findings show that Perceived Innovation Characteristics (PIC) play a central role in translating contextual conditions into behavioral intention, highlighting that adoption decisions are shaped through perception formation under real-world constraints.

Policy and Practical Recommendations

The findings provide several practical implications for policy and extension design. First, technology promotion programs should prioritize **demonstration-based learning**, such as on-farm demonstration plots and peer learning systems, to enhance observability and reduce uncertainty. Second, **subsidized trial programs** or shared-service models (e.g., drone service providers) should be expanded to lower entry barriers for smallholder farmers who face financial and scale constraints. Third, extension systems should shift toward **hands-on training and continuous support**, particularly for older farmers with limited formal education, rather than relying solely on information dissemination. Finally, interventions should be tailored to reflect differences between technology types, recognizing that capital-intensive technologies (e.g., drones) and process-based technologies (e.g., microorganisms) require different adoption pathways and support mechanisms.

Future Research Directions

Future research should extend this study in several directions. First, expanding the analysis to larger and multi-regional samples would improve the generalizability of the findings across different agricultural systems. Second, longitudinal designs are needed to capture dynamic changes in perception and adoption behavior over time. Third, multi-group analysis could be applied to compare adoption mechanisms across different farmer segments, such as farm size, age groups, or levels of technology experience. Finally, future studies may integrate additional economic and institutional variables—such as market access, price volatility, and service availability—to further refine the understanding of adoption mechanisms under real-world constraints.

Limitations

First, the use of a **cross-sectional design** limits the ability to establish long-term causal relationships. Although SEM captures structural mechanisms, it cannot fully trace learning dynamics and actual usage patterns across multiple production seasons.

Second, the study relies entirely on **self-reported data**, which may be subject to social desirability bias or inaccuracies in self-assessment.

Third, the research was conducted in the **Northeastern region of Thailand**, characterized by specific farm structures, community networks, and organic rice market conditions. Therefore, generalization to other geographical or institutional contexts should be undertaken with caution.

AI Disclosure Statement

The authors used artificial intelligence (AI)-assisted tools solely for language refinement and improving academic clarity. The AI tools were not used for data analysis, interpretation of results, or generation of original scientific content. All content, analysis, and conclusions were developed and verified entirely by the authors.

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