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Thai Dairy Farmers' Adoption of Automated Disinfectant Production

Akkhawit Akkhasingh, Sujira Vuthisopon*, Amnuay Saengnoree, Somchai Sonsupap

College of Innovation and Industrial Management, King Mongkut's Institute of Technology Ladkrabang (KMITL), Bangkok, Thailand. *Corresponding Author's Email: ajarnsujirakmitl@gmail.com, sujira.vu@kmitl.ac.th

Abstract

Adoption of sustainable on-farm technologies is essential to minimize environmental impacts and improve the sustainability and biosecurity of the livestock industry. Despite growing interest in precision livestock farming, no prior study has examined the psychological and behavioral determinants of dairy farmers' adoption of automated disinfectant production systems, particularly in developing economies. The current research uses structural equation modeling to investigate the determinants of adoption intention for a novel automated on-farm disinfectant production system that requires minimal external chemicals and generates no waste. The data were gathered from 320 members of the Dairy Farming Cooperative of Thailand. The hypothesized model includes the constructs of innovation characteristics, trust in innovation, perceived usefulness and perceived value to explain adoption intention. The model had a good fit (χ^2/df = 1.22, RMSEA = 0.02, CFI = 0.99) and accounted for 73% of the variability in adoption intention. Among the variables studied, perceived value showed the strongest direct influence on adoption, followed by perceived usefulness. In addition, innovation characteristics exerted the greatest overall influence on adoption intention through the intermediary factors of trust, perceived usefulness and perceived value. It becomes evident that, to foster sustainable innovation in agriculture, it is essential to convey a value proposition that goes well beyond its functional aspects, with trust an indispensable factor in the process. The outlined model provides theoretical and practical views that can enhance the implementation of innovative livestock management techniques.

Keywords: Adoption Intention, Dairy Farm Management, Innovation Diffusion, Precision Livestock Farming (PLF), Sustainable Agriculture, Thailand.

Introduction

The world's livestock industry, especially the dairy subsector, is experiencing unprecedented changes driven by technological advancements, shifting socio-economic dynamics and increased sustainability requirements (1-5). PLF technologies are continually advocated for improved productivity, animal well-being and efficiency, as well as for meeting sustainability objectives (2, 6). On the other hand, issues such as greenhouse gas emissions, water usage, land degradation, development of antimicrobial resistance and animal welfare have come under heavy criticism in the livestock industry (7-10). The need of the hour is thus the creation of sustainable production processes that ensure economic profitability without neglecting social responsibilities. In light of these challenges, efforts have been initiated in many nations to promote the use of clean production technologies and precision agriculture in livestock enterprises (11). Some of these technologies include automated feeders, environmental sensors, disease surveillance technology and bio-security management technology (5, 12-14). These technologies can enhance production efficiency, reduce costs, improve disease prevention and provide a more sustainable way to manage livestock. Nonetheless, even with all the technological advancements witnessed in recent times, farmers have been rather hesitant to adopt some of these innovations (15-18). The adoption of agricultural innovations has been found to depend not only on the capacity of these innovations but also on behavioral and psychological factors (19-22). Farmers' choice of innovations is usually based on considerations such as usefulness, reliability, economic value, compatibility with current methods, simplicity and trustworthiness of the technology provider (12, 23, 24). This means that having better capacity does not necessarily imply successful adoption. On the

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contrary, adoption is determined by a cognitive process in which farmers judge whether the innovation can really improve their operations without risk.

Among the many advances in agriculture, the development of automated disinfectant production systems for dairy cows stands out as an innovative approach that combines biosecurity management, sustainable development and efficiency (25). Proper disinfection systems are key to preventing and managing disease on dairy cattle farms. Automated disinfectant production systems can increase sanitation levels, reduce labor costs, conserve chemical use and enhance biosecurity protocols on farms.

Past studies on the use of agricultural technology have mostly focused on smart farming, digital agriculture, machinery adoption and precision monitoring. There has been increased use of structural equation modeling (SEM) to analyze how various psychological, technological and behavioral variables affect the adoption of agricultural technologies. Limited research has been conducted on biosecurity technologies, especially automatic disinfection systems for dairy farms.

This research aims to fill this knowledge gap by formulating and empirically testing a structural equation model to examine the factors that determine dairy farm owners' intention to adopt automation for disinfectant production (18, 26). In developing this theoretical framework, the current research draws on the ideas of Diffusion of Innovations (DOI) theory and the Technology Acceptance Model (TAM) (20, 22, 27-31). According to the DOI theory, innovation adoption is influenced by features such as relative advantage, compatibility, complexity, observability and trialability (32). On the other hand, TAM emphasizes the role of usefulness perception in determining behavioral intention to adopt technology (33).

There are five major constructs in the proposed model, namely innovation characteristics (IC), trust in innovation (TI), perceived usefulness (PU), perceived value (PV) and adoption intention (AI). According to the conceptual model, positive perceptions of innovation characteristics enhance trust and perceptions of usefulness. Moreover, trust in innovation is believed to enhance perceptions of usefulness and value, which, in turn, lead to adoption intention.

In terms of contributions to the existing literature, there are three major contributions. Firstly, the study adds theoretical value by integrating DOI theory, TAM and value constructs into a single conceptual framework tailored for automated disinfectant technology adoption in the dairy farming context. To the best of the current knowledge, such constructs combined have not been used in previous studies on automated disinfectant production systems. Secondly, the study contributes methodologically by using a bootstrapped mediation analysis based on 5,000 resampled datasets and bias-corrected confidence intervals. Finally, this research makes an empirical contribution by considering an understudied target population consisting of 320 Thai dairy farmers. Accordingly, the study aims to:

(a) Develop and validate a comprehensive SEM explaining factors affecting dairy farmers' adoption intention toward automated disinfectant production technology.

(b) Examine the causal relationships and relative effects among innovation characteristics, trust in innovation, perceived usefulness, perceived value and adoption intention.

The following hypotheses were proposed:

H1a: Innovation Characteristics (IC) positively affect Perceived Usefulness (PU).

H1b: Innovation Characteristics (IC) positively affect Perceived Value (PV).

H1c: Innovation Characteristics (IC) positively affect Trust in Innovation (TI).

H2a: Trust in Innovation (TI) positively affects Perceived Usefulness (PU).

H2b: Trust in Innovation (TI) positively affects Perceived Value (PV).

H3a: Perceived Usefulness (PU) positively affects Adoption Intention (AI).

H3b: Perceived Usefulness (PU) positively affects Perceived Value (PV).

H4: Perceived Value (PV) positively affects Adoption Intention (AI).

Consistent with the principles of mediation theory, there should be no direct relationship between innovation characteristics and adoption intention, as the relationship is indirect via trust, usefulness and value perception. These results inform policymakers, agricultural institutions and technology manufacturers in developing appropriate interventions to support the sustainable adoption of innovations in biosecurity management within the dairy industry.

Methodology

Research Design and Population

A cross-sectional, quantitative survey method was used for this study to examine a proposed structural model. The focus was on active members of the Dairy Farming Cooperative of Thailand who were part of operational decision-making and potential users of automated disinfectant technology. This group is critical to introducing sustainable production technologies into the Thai dairy industry.

Sampling Frame, Technique and Sample Size Justification

However, several limitations in the research limit the ability to generalize from the results obtained in the Thai population as a whole. For example, non-probability sampling, including quota and convenience sampling, is subject to selection bias. The sampling frame consisted of membership lists from the three major dairy cooperatives in Thailand: Nong Pho Ratchaburi Cooperative, Ratchaburi Province (n = 138), Waritchaphum Cooperative, Sakon Nakhon Province (n = 92) and Kham Thale So Cooperative, Nakhon Ratchasima Province (n = 90) with approximate GPS coordinates 13.73° N 99.91° E, 17.13° N 103.39° E and 14.96° N 101.93° E respectively.

Geographical dispersion among farmers was the main obstacle to conducting probability sampling. Consequently, a two-step sampling method was applied, which involved quota sampling based on the number of cooperative members (total frame = 5,757; total sample = 320; sampling ratio = 5.26%) and convenience sampling within quotas. However, non-probability sampling methods, including quota and convenience sampling, are prone to selection bias, which can affect the generalizability of findings (34).

Data were collected through meetings and extension activities with farmers, either through paper surveys or Google forms with QR codes. Sampling involved participants who attended the meetings and consented to take part, as in other adoption studies in agriculture. Age, level of education and years of experience were collected but not included in the SEM analysis.

Sample Size Determination

The sample size was determined based on the requirement for sufficient power to run an SEM with latent variables. The minimum sample size should be between 10 and 20 per estimated parameter (35). For our study with 16 variables and parameter estimation, we needed at least 160-320 participants. The researchers targeted the higher end of the range (n = 320) because the bootstrapping procedure provided increased stability and statistical power. The chosen sample size is not only larger than the minimum required for maximum likelihood estimation but also sufficient for stable confidence interval estimation via bootstrapping (36).

Handling of Incomplete Responses

All 320 returned questionnaires were fully completed and suitable for analysis. Missing data were negligible (<1% across all variables) and were imputed using the mean. Little's MCAR test confirmed that missing values were missing completely at random ($\chi^2 = 12.7$, df = 18, $p = 0.81$). Given the minimal proportion of missing data, this approach does not bias parameter estimates and follows recommended practices in agricultural technology adoption research.

Measurement Instrument and Pre-Testing

The development of the survey questionnaire was done using several steps as follows:

(a) Item generation: Items for each construct, IC, TI, PU, PV and AI and their dimensions, were developed based on reliable scales in technology adoption and perceived value literature (20-22), customized to fit in automatic disinfection.

(b) Content validity and face validity: Five experts, with knowledge in agricultural technology (two), veterinary science (two) and survey research (one), reviewed the questionnaire and rated the clarity and validity of the items. The Index of Item-Objective Congruence (IOC) was calculated for all items, yielding scores ranging from 0.80 to 1.00, indicating excellent content validity.

(c) Pilot study and reliability: The pilot test consisted of 30 dairy farmers outside the sample group. Cronbach's Alpha coefficients for all multi-item constructs ranged from 0.83 to 0.89, implying good to excellent internal consistency reliability (37). Item Discrimination

Indices were also determined for all questionnaire items and ranged from 0.60 to 0.78, within an acceptable range.

(d) Final instrument: The final questionnaire consisted of six sections: (i) Demographic and farm characteristics, (ii) Current disinfectant use practices and (3-6) Five-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree) measuring the five main constructs. Mean score evaluation criteria and interpretation used a five-level Likert-type opinion scale in which 5 was "I strongly agree." [4.50–5.00], 4 was "I agree." [3.50–4.49], 3 was "I am unsure." [2.50–3.49], 2 was "I disagree." [1.50–2.49] and 1 was "I strongly disagree." [1.00–1.49] (38).

Conceptual Definitions of Latent Variables

The five latent variables in this study are defined as follows:

(a) Innovation characteristics: Farmers' perceptions of the automated disinfection system's relative advantage, compatibility, complexity, trialability and observability (22).

(b) Trust in innovation: Farmers' confidence that the automated disinfection system will perform reliably, safely and as promised (12).

(c) Perceived usefulness: Farmers' belief that using the automated disinfection system will improve farm efficiency, reduce labor and enhance biosecurity (20).

(d) Perceived value: Farmers' holistic assessment of the net benefits of the automated disinfection system, balancing economic, environmental and practical considerations.

(e) Adoption intention: Farmers' stated likelihood of implementing the automated disinfection system on their farm within the next 12 months (16, 17).

Data Collection and Control for Common Method Bias (CMB)

The survey data collection procedure involved conducting face-to-face paper-based surveys with trained enumerators at cooperative meetings. Given the nature of the cross-sectional self-report measures employed in this study, common method bias was controlled using both procedural and statistical controls (39). First, anonymity among respondents was ensured to reduce evaluation apprehension and the questionnaire items were randomized to reduce response-set bias. Second, Harman's one-factor test was conducted as an initial screening process (40). The unrotated exploratory factor analysis (EFA) indicated that the first factor accounted for 28.7% of the variation, below the 50% threshold, suggesting that CMB is not a major concern in the study. Furthermore, the full collinearity diagnosis approach was followed (41). It was found that all VIF values for the latent variables in the research model were below the conservative threshold of 3.3.

Data Analysis Strategy

Analysis proceeded in four sequential stages using LISREL 9.10 (Scientific Software International, Lincolnwood, IL, USA) and IBM SPSS Statistics for Windows, Version 26.0 (IBM Corp., Armonk, NY, USA). Frequencies, percentages, means (M) and standard deviations (SD) were calculated for sample characteristics and construct scores. Before testing the SEM, a CFA was conducted to assess the construct validity of the five latent variables (42). The study's authors evaluated:

Convergent validity: Using factor loadings (>0.50), Average Variance Extracted (AVE > 0.50) and Composite Reliability (CR >0 .70) (43).

Discriminant validity

By ensuring the square root of each construct's AVE was greater than its correlation with other constructs (Fornell-Larcker criterion) and that heterotrait-monotrait (HTMT) ratios were below 0.90 (44).

Model fit: Using a suite of indices: χ^2/df < 3, RMSEA < 0.08, SRMR < 0.08, CFI >0 .90, TLI >0 .90 and GFI >0.90 (45).

SEM and Hypothesis Testing

After establishing the measurement model's validity, the structural model was evaluated. Specifically, the path coefficients (standardized beta, β), along with their levels of statistical significance (t-value > 1.96 for $p < 0.05$), were evaluated against our hypotheses H1 to H4. The model's explanatory strength was evaluated using R^2 values for the endogenous variables. No direct path between IC and AI exists in the proposed structural model, indicating that our conceptual model is fully mediated.

Analysis for Indirect Effect and Path Stability

To perform an exhaustive analysis of the indirect effects or mediation in our model (IC→TI→PU) and to accommodate any non-normality in our dataset, we have used non-parametric bootstrapping (46). Our dataset consisted of 320 observations. For each variable, 5000 bootstrap samples (with replacement) were drawn from the original data and the corresponding 95% confidence intervals were obtained. If the bootstrap CI for any effect contains 0, it implies that the effect is not significant at $p < 0.05$.

Results

Sample Characteristics and Current Practices

As shown in Table 1, the sample consisted of 320 dairy farmer decision-makers from major dairy cooperatives in Thailand. The respondents were relatively balanced by gender, with 50.31% female and 49.69% male participants. Most respondents were of working age, particularly aged 21 to 40 (64.06%), indicating that the sample largely represented active members involved in dairy farming operations. In addition, more than half of the respondents held at least a bachelor's degree and the majority had more than five years of dairy farming experience. Table 1 further indicates that the respondents possessed substantial professional experience in dairy farming. Approximately 84.00% had more than five years of experience, suggesting that the participants were familiar with farm management and biosecurity practices. The respondents' educational and professional backgrounds support the reliability of the data collected for evaluating perceptions of automated disinfectant technology adoption.

Table 1: Sample Demographic and Professional Characteristics (n=320)

Characteristics of the sample group	Farmers	%
Gender		
Male	159	49.69
Female	161	50.31
Age		
under 20 years of age	25	7.81
21-30 years old	105	32.81
31-40 years old	100	31.25
41-50 years old	56	17.50
51-60 years old	21	6.56
over 60 years of age	13	4.07
Education Level		
Below Bachelor's Degree	150	46.88
Bachelor's Degree	159	49.68
Higher than a Bachelor's Degree	11	3.44
Dairy Farming Experience		
Less than 5 years	51	15.94
5 - 10 years	115	35.94
11 - 15 years	93	29.06
16 - 20 years	52	16.25
More than 20 years	9	2.81

Note: n = number of respondents; % = percentage of respondents.

As presented in Table 2, current disinfectant practices revealed that biosecurity activities were regularly implemented on participating dairy farms. Most respondents reported using disinfectants between three and six times per week (64.06%), indicating a relatively high level of concern regarding disease prevention and farm sanitation. The findings also show that disinfectant use was mainly associated with external sanitation and barn cleaning activities. Table 2 additionally demonstrates that chlorine-based disinfectants (33.12%) and aldehyde-based disinfectants (25.00%) were the most used chemical agents. This pattern suggests that dairy farmers are already familiar with biosecurity technologies and chemical sanitation procedures, which may support the future adoption of automated disinfectant systems.

Table 2: Current Disinfectant Use Practices on Participating Farms (n = 320)

Information on the use of disinfectants on farms	Farmers	%
Frequency of Disinfectant Use on the Farm		
Used daily	62	19.38
Used 1–2 times per week	19	5.94
Used 3–4 times per week	95	29.69
Used 5–6 times per week	110	34.37
Used only when cattle are sick	34	10.62
Totals	320	100
Type/Category of Disinfectant Use on the Farm		
External disinfection (e.g., foot baths, farm entrance)	134	41.88
Barn and equipment disinfection	98	30.63
Animal-related disinfection (e.g., teat dip, wound care)	53	16.56
Disinfection for special situations (e.g., disease outbreak)	35	10.93
Totals	320	100
Type of Disinfectant Agent Used on the Farm		
Quaternary ammonium compounds	39	12.19
Aldehyde group (e.g., glutaraldehyde, formaldehyde)	80	25.00
Chlorine group (e.g., hypochlorite)	106	33.12
Iodine group (e.g., iodophors)	76	23.75
Organic/Inorganic acids	19	5.94
Totals	320	100

Note: n = number of survey responses or participating farm units; % = percentage of respondents.

Measurement Model Validation

As shown in Table 3, all latent constructs recorded mean scores above the midpoint of the Likert scale, ranging from 3.71 to 4.27. Confirmatory factor analysis demonstrated excellent model fit, with $\chi^2/df = 1.22$, RMSEA = 0.02, SRMR = 0.03, CFI = 0.99, TLI = 0.99, GFI = 0.98 and AGFI = 0.94. These indices indicate that the proposed measurement model was statistically appropriate and well-fitted to the observed data.

Table 3 further confirms the measurement model's reliability and validity. Composite reliability values ranged from 0.83 to 0.86, exceeding the recommended threshold of 0.70. In addition, all average variance extracted (AVE) values were above 0.50 and standardized factor loadings exceeded 0.60, indicating satisfactory convergent validity. Discriminant validity was also confirmed through both the Fornell–Larcker criterion and HTMT ratios below 0.85.

Table 3: Construct Reliability (CR), Convergent Validity (CV) and Discriminant Validity (DV)

Construct	CR	AVE	IC	TI	PU	PV	AI
IC	0.83	0.62	0.79				
TI	0.85	0.66	0.68	0.81			
PU	0.83	0.62	0.67	0.60	0.79		
PV	0.86	0.60	0.64	0.43	0.58	0.77	
AI	0.85	0.65	0.54	0.35	0.42	0.57	0.81
HTMT Ratios							
IC	–	–	–				
TI	–	–	0.82	–			
PU	–	–	0.83	0.74	–		
PV	–	–	0.80	0.52	0.71	–	
IA	–	–	0.68	0.43	0.52	0.70	–

Note: CR = Composite Reliability; AVE = Average Variance Extracted; IC = Innovation Characteristics; TI = Trust in Innovation; PU = Perceived Usefulness; PV = Perceived Value; AI = Adoption Intention; HTMT = Heterotrait–Monotrait Ratio. Values on the diagonal represent the square roots of the AVEs.

Structural Model and Hypothesis Testing

As presented in Table 4, the structural model also demonstrated excellent goodness-of-fit indices, including $\chi^2/df = 1.22$, RMSEA = 0.02, SRMR = 0.03, CFI = 0.99, GFI = 0.98 and AGFI = 0.94. The model explained 73% of the variance in adoption intention ($R^2 = 0.73$), indicating strong predictive capability. Furthermore, all variance inflation factor (VIF) values were below 3.0, confirming the absence of multicollinearity among the predictor variables.

Table 4 indicates that all direct-effect hypotheses were statistically supported. Innovation Characteristics significantly influenced Trust in Innovation, Perceived Usefulness and Perceived Value. Trust in Innovation also strongly predicted both Perceived Usefulness and Perceived Value. Moreover, both Perceived Usefulness and Perceived Value significantly influenced Adoption Intention, with Perceived Value demonstrating the strongest direct effect.

From Table 4, the mediation analysis using 5,000 bootstrap resamples revealed full sequential mediation effects. The influence of Innovation Characteristics on Adoption Intention was mediated by Trust in Innovation, Perceived Usefulness and Perceived Value. Similarly, the effect of Trust in Innovation on Adoption Intention was fully mediated by Perceived Value. These findings support the theoretical relationships proposed in the structural model.

Table 4: Direct, Indirect and Total Effects with Bootstrap Confidence Intervals

Path	Effect Type	β	Bootstrap SE	95% BC CI	p-value
IC → TI	Direct	0.63	0.081	[0.48, 0.78]	<0.001
IC → PU	Direct	0.34	0.112	[0.12, 0.56]	0.002
	Indirect (via TI)	0.32	0.048	[0.24, 0.43]	<0.001
	Total	0.66	0.089	[0.49, 0.83]	<0.001
IC → PV	Direct	0.20	0.094	[0.02, 0.38]	0.033
	Indirect (via TI, PU)	0.52	0.062	[0.40, 0.64]	<0.001
	Total	0.72	0.075	[0.57, 0.87]	<0.001
IC → AI	Indirect only	0.63	0.059	[0.52, 0.75]	<0.001
TI → PU	Direct	0.51	0.124	[0.27, 0.75]	<0.001
TI → PV	Direct	0.51	0.116	[0.28, 0.74]	<0.001
	Indirect (via PU)	0.16	0.035	[0.10, 0.24]	0.002
	Total	0.67	0.093	[0.49, 0.85]	<0.001
TI → AI	Indirect only	0.55	0.062	[0.43, 0.67]	<0.001
PU → PV	Direct	0.31	0.124	[0.07, 0.55]	0.012
PU → AI	Direct	0.32	0.158	[0.01, 0.63]	0.043
	Indirect (via PV)	0.18	0.045	[0.10, 0.28]	0.001
	Total	0.50	0.148	[0.21, 0.79]	<0.001
PV → AI	Direct	0.57	0.153	[0.27, 0.87]	<0.001

Note: BC CI = Bias-Corrected Confidence Interval based on 5,000 bootstrap samples; SE = Standard Error; IC = Innovation Characteristics; TI = Trust in Innovation; PU = Perceived Usefulness; PV = Perceived Value; AI = Adoption Intention. "Indirect only" indicates that no direct path was hypothesized in the structural model. *p < 0.01.

As shown in Table 5, all eight hypotheses were statistically supported at $p < 0.01$. The standardized path coefficients indicate that Innovation Characteristics, Trust in Innovation, Perceived Usefulness and Perceived Value all played significant roles in influencing adoption intention toward automated disinfectant technology.

Figure 1 presents the final structural model with standardized path coefficients. The strongest relationships were observed between Innovation Characteristics and Trust in Innovation and between Perceived Value and Adoption Intention. These findings confirm the robustness of the proposed conceptual framework and demonstrate the importance of trust and perceived value in technology adoption behavior.

Table 5: Final Hypotheses Testing

Hypotheses	Path (Direct Effect)	Std. Estimate (β)	t-value	Result	Conclusion
H1a	Innovation Characteristics → Perceived Usefulness	0.34**	3.03	Significant	Supported
H1b	Innovation Characteristics → Perceived Value	0.20**	2.12	Significant	Supported
H1c	Innovation Characteristics → Trust in Innovation	0.63**	7.80	Significant	Supported
H2a	Trust in innovation → Perceived Usefulness	0.51**	4.10	Significant	Supported
H2b	Trust in innovation → Perceived Value	0.51**	4.39	Significant	Supported
H3a	Perceived Usefulness → Adoption Intention	0.32**	2.03	Significant	Supported
H3b	Perceived Usefulness → Perceived Value	0.31**	2.49	Significant	Supported
H4	Perceived Value → Adoption Intention	0.57**	3.72	Significant	Supported

Note: β = standardized path coefficient. **p < 0.01.

As shown in Figure 1, the final structural equation model demonstrated strong relationships among the proposed constructs related to automated disinfectant technology adoption. Innovation Characteristics (IC) significantly influenced Trust in Innovation (TI), Perceived Usefulness (PU) and Perceived Value (PV), indicating that positive perceptions of the innovation enhanced both trust and perceived benefits of the technology. Trust in Innovation also exerted substantial effects on both Perceived Usefulness and Perceived Value.

Figure 1 further illustrates that Perceived Value had the strongest direct influence on Adoption Intention (AI) (β = 0.57), followed by Perceived Usefulness (β = 0.32). These findings suggest that dairy farmers' intention to adopt automated disinfectant technology depended primarily on the perceived practical and economic value of the system. The structural model explained 73% of the variance in Adoption Intention (R^2 = 0.73), demonstrating strong predictive power.

From Figure 1, all hypothesized paths were statistically significant at $p < 0.01$. The standardized factor loadings for all observed indicators were also above acceptable thresholds, confirming the reliability of the measurement items used for each construct. Overall, the findings support the proposed conceptual framework and validate the important roles of innovation characteristics, trust, usefulness and perceived value in influencing technology adoption behavior among dairy farmers.

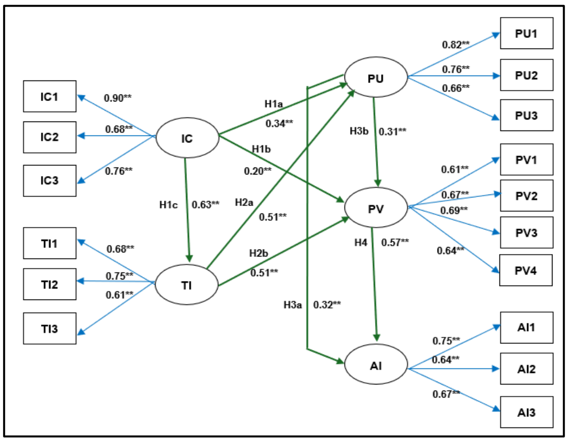

Figure 1: Final Structural Model with Standardized Path Coefficients

(χ^2 = 42.83; df = 35; p = 0.17; χ^2/df = 1.22; RMSEA = 0.02; SRMR = 0.02; CFI = 0.99; GFI = 0.98; AGFI = 0.94. R^2 for AI = 0.73. IC = Innovation Characteristics; TI = Trust in Innovation; PU = Perceived Usefulness; PV = Perceived Value; AI = Adoption Intention. **p < 0.01)

Discussion

This study investigated factors influencing Thai dairy farmers' intention to adopt an automated disinfectant production system. The model explained 73% of the variance in adoption intention, confirming that adoption follows a sequential psychological process rather than a single decision event (47).

Holistic Interplay of Factors (RQ1)

Adoption intention occurs via a series of evaluations involving three steps. Firstly, farmers form initial impressions of the innovations based on their attributes. Secondly, the attributes foster trust in the innovation, a process that becomes increasingly essential given biosecurity concerns and financial implications (48). Finally, trust leads to perceptions of the innovation's usefulness, thereby driving adoption intention. It is for this reason that many advanced innovations fail to gain widespread adoption.

Specific Pathways and Effect Strengths (RQ2)

The effects of innovation characteristics were the strongest ($\beta = 0.63$) in influencing adoption intention, but were completely indirect, through trust, usefulness and value. This proves that technical advantages alone are not enough, because farmers need to recognize the value of innovations beyond mere functionality.

Trust is a mediating factor that directly influences both perceived usefulness ($\beta = 0.51$) and perceived value ($\beta = 0.51$). Trust alleviates concerns about innovative biosecurity technologies and enables farmers to understand their benefits (48).

The most influential predictor of adoption intentions is the perceived value ($\beta = 0.57$), followed by perceived usefulness ($\beta = 0.32$). Thus, the farmers consider the economic, ecological and practical factors of innovations instead of just efficiency.

These results further develop the technology acceptance model and diffusion of innovation theory by proving that value perception acts as a mediator in the trust-adoption relationship in agriculture (49).

Conclusion

This paper examines and validates a structural model of the adoption intention for automated disinfectant production technology among Thai dairy farmers. It shows that adoption intention involves a chain of processes characterized as follows: innovation characteristics → trust → perceived usefulness → perceived value → adoption intention. Perceived value had the greatest direct impact on adoption intention, while innovation characteristics had the greatest indirect impact. Technical superiority is not enough; rather, the farmer must trust the technology and understand its value across dimensions, such as economic, environmental and practical.

Practice-wise, the focus should be on designing demonstration programs to increase farmers' confidence in the technology. The shortcomings of the present research include non-probability sampling, which means the study was conducted with three cooperatives in central and northeastern Thailand and a cross-sectional research design. The future direction of further research includes validation of the model geographically and longitudinally.

The current study has limitations that hinder the generalizability of its results to the wider Thai population. First, the researcher's sampling method in this case, non-probability sampling through quota and convenience sampling, is prone to selection bias. It is plausible that farmers who attend cooperative meetings differ from those who do not in terms of their engagement level, interest in technology and size. This implies that the possibility of technology's positive contribution to productivity may overestimate the average productivity of Thai dairy farmers. Therefore, the model's high explanatory power ($R^2 = 73\%$) may apply only to more engaged farmers, not to the general population. Second, the sampling exercise included only three cooperatives in Thailand's central and northeastern regions. The conclusions derived from this research cannot be generalized to the rest of Thailand.

Abbreviations

AI: Adoption Intention, IC: Innovation Characteristics, PU: Perceived Usefulness, PV: Perceived Value, SD: Standard Deviation, SEM: Structural Equation Modeling, TI: Trust in Innovation.

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Author Contributions

Akkhawit Akkhasingh: Conceptualization, Methodology, Software, Supervision, Data Curation, Writing—Review and Editing, Validation, Investigation, Resources, Writing—Original Draft Preparation, Visualization, Sujira Vuthisopon: Conceptualization, Methodology, Software, Supervision, Data Curation, Writing—Review and Editing, Formal Analysis, Visualization, Amnuay Saengnoree: Formal Analysis, Visualization, Project Administration, Somchai Sonsupap: Formal Analysis, Visualization, Funding Acquisition. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

During the preparation of this manuscript, the authors used ChatGPT to assist in translating the original content from Thai to English. Grammarly Premium was used to refine language prior to submission. No AI tools were used to generate the study's conceptual framework, data, analysis, or interpretations. All content, including figure accuracy and underlying academic meaning, was reviewed and verified by the authors, who take full responsibility for the integrity of the work.

Ethics Approval

This study recruited adult dairy farmers in Thailand on a voluntary basis. No sensitive information was collected and the study posed no physical or mental risks. Written or electronic informed consent was obtained from all participants. The study complied with the Declaration of Helsinki (2013) and Thai national guidelines for exempt social science research (50). No personal identifiers were collected and participants could withdraw at any time without consequence.

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