OBSTACLES TO ADOPTING TECHNOLOGY IN THE THAI AGRICULTURAL SECTOR AND THEIR INTEGRATION INTO THE TECHNOLOGY ACCEPTANCE MODEL

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ABSTRACT

This study examines the obstacles to technology adoption in the agricultural sector of southern Thailand, focusing on four provinces: Nakhon Si Thammarat, Trang, Phatthalung, and Songkhla. A survey of 193 farmers revealed a high rate of smartphone ownership (95.3%), suggesting strong potential for mobile-based agricultural tools. Key factors influencing adoption included attitudinal factors, perceived ease of use, and perceived usefulness being the most significant predictors of adoption and increased productivity. The study also noted that most respondents were middle-aged and highly educated, which might limit the generalizability of the findings. Adoption attitudes varied across different income levels, age groups, and educational backgrounds. The study recommends emphasizing the practical benefits and ease of use of new technologies, adopting mobile-first strategies, and tailoring outreach efforts to different demographics. These findings contribute to a better understanding of technology adoption in Thai agriculture and offer guidance for future research and policy development aimed at enhancing technological uptake.

KEY WORDS: AGRICULTURAL TECHNOLOGY ADOPTION/ TECHNOLOGY ACCEPTANCE MODEL (TAM)/ FARM TECHNOLOGY OBSTACLES/ THAI FARMING PRACTICES

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CHAPTER I
INTRODUCTION

1.1 Background of Study

Agriculture has always played an essential role in the economy and society of southern Thailand. Approximately 60% of the southern part of Thailand is an agricultural area; the majority of people in this area are in the agricultural sector, which is the largest source of employment and a primary source of income for rural households. However, agriculture sectors still apply traditional farming methods. At the same time, Environmental degradation and climate change, such as soil erosion, water scarcity, droughts, floods, and unpredicweather conditions, exacerbate the vulnerabilities of the agriculture sector, and these pose significant threats to agricultural productivity. Moreover, the aging population of farmers is a trend that is increasing critical issues due to the decline of incomes, making younger generations move to urban regions in pursuit of improved job prospects and increased income in industries and services. This aging population of farmers is leading to a decline in crop yield, productivity, revenue, and economic contribution to Thailand's farmers because aging farmers find it hard to adopt new technologies and innovative practices due to their being less knowledgeable. To increase the productivity and quality of sustainable Thai agricultural products, integrating technology into agriculture can potentially transform the Thai agricultural sector significantly.

However, integrating technology into the Thai agriculture sector is difficult because many farmers lack technical knowledge and skills for new technologies. Traditional farming practices dominate the industry, and transitioning to modern methods involves a steep learning curve. Farmers need comprehensive training programs and continuous support to use and maintain new technologies effectively.

Therefore, to enhance the adoption of new technologies in the Thai agriculture industry, the Technology Acceptance Model (TAM) will be applied. TAM provides a framework to understand the elements affecting farmers' adoption and utilization of new technologies, highlighting Perceived Usefulness (PU) and Perceived

Ease of Use. (PEOU). TAM helps identify and address the key determinants that facilitate technology adoption.

1.2 Problem statement

The agricultural sector in southern Thailand, particularly in Nakhon Si Thammarat, Trang, Phatthalung, and Songkhla, is facing significant challenges due to its reliance on traditional farming methods. Despite its historical importance, the sector's contribution to GDP is declining. Through personal observation in these provinces, many farms continue to be operated by aging farmers who resist adopting modern technologies because of insufficient knowledge, skills, and necessary infrastructure.

This resistance can be broken down into four key obstacles:

1. Aging Farmer Population: As younger generations migrate to urban areas, the farming population is aging, leading to labor shortages and reduced productivity.
2. Reliance on Traditional Methods: Most farmers still use outdated practices, limiting agricultural output and quality.
3. Lack of Technical Knowledge and Skills: The transition to modern technology is challenging due to insufficient training and support.
4. Infrastructure Deficiencies: Limited access to reliable electricity and internet connectivity hampers technology adoption.

Therefore, integrating modern technology is crucial for improving productivity and sustainability. The Technology Acceptance Model (TAM) offers understanding of how perceived usefulness (PU) and perceived ease of use (PEOU) affect farmers' willingness to adopt technology, thereby addressing these challenges more effectively.

1.3 Research Objective

This research aims to investigate an obstacles and facilitators in adopting modern agricultural technologies in the southern Thai farm sector, focusing on Nakhon Si Thammarat, Trang, Phatthalung, and Songkhla. Specifically, the research objectives are to:

1. Identify obstacles that Thai farmers face, such as sticking to old farming methods, aging farmers, a lack of skills, and poor infrastructure.
2. To evaluate Benefits how using modern technology can boost productivity, sustainability, and economic growth.
3. To apply the TAM Model to understand what makes farmers more likely to accept new technology, focusing on how useful and easy they think it is.
4. To propose Solutions or Suggest ways to overcome obstacle, like training programs, financial help, better infrastructure, and policy changes.
5. To measure Effectiveness and how well TAM-based strategies work in helping Thai farmers adopt technology and show how relevant the model is in agriculture.

1.4 Research Question

1. What are the primary challenges faced by farmers in southern Thailand when adopting modern agricultural technologies, including the reliance on traditional practices, environmental issues, aging demographics, lack of technical knowledge, and infrastructure deficiencies?
2. How does the adoption of contemporary or modern agricultural technologies impact the productivity, sustainability, and economic contribution of the agricultural sector in southern Thailand?
3. How do perceived usefulness (PU) and perceived ease of use (PEOU), as defined by using the Technology Acceptance Model (TAM), influence farmers' decisions to adopt new agricultural technologies?
4. How effective is the application of TAM-based approaches in promoting the adoption of contemporary or modern agricultural technologies among Thai farmers?

CHAPTER II
LITERATURE REVIEW

2.1 Introduction

The adoption of technology in agriculture is crucial for enhancing productivity, sustainability, and economic viability. This literature review explores the obstacles to technology adoption in the Thai agricultural sector and integrates the Technology Acceptance Model (TAM) to understand these challenges.

2.2 Barriers or Obstacles to Technology Adoption

Several studies have identified various obstacles to the adoption of technology in agriculture. These obstacles can be broadly categorized into knowledge and awareness, technical skills, infrastructure, financial constraints, and socio-cultural factors. Smith (2003) highlighted that the choice of technology is heavily influenced by knowledge and general awareness. Farmers often lack the necessary information about new technologies and their benefits, which hinders adoption (Rezaei, Kurosh, Salehi, and Saeid, 2010), (Kumari, Sneha, Shirish, and Yogesh, 2018) emphasized the importance of awareness and understanding of technology, noting that a lack of information and expertise significantly impedes technology adoption (Rezaei, Kurosh, Salehi, and Saeid, 2010). In terms of Technical Skills, the lack of technical skills is a major obstacle in the agricultural sector. Many farmers do not possess the skills required to operate and maintain new technologies, which limits their ability to adopt these innovations effectively (Rezaei, Kurosh, Salehi, and Saeid, 2010). This is particularly evident in the context of digital technologies, as observed by Sayruamyat and Nadee (2020) in their study of digital literacy among Thai farmers. Infrastructure, inadequate infrastructure, especially in rural areas, poses a significant challenge to technology adoption. Reliable electricity and internet connectivity are essential for operating advanced agricultural technologies, and their absence can be a major deterrent (Rezaei-Moghaddam & Salehi, 2010). This significant in the realm of smart farming technologies, as noted by Jaroenwanit et al. (2023). Financial limitations represent a significant obstacle to technology adoption. The substantial expenses related to obtaining and sustaining new technologies, coupled with limited access to credit, make it difficult for many farmers to invest in modern agricultural tools (Rezaei-Moghaddam & Salehi, 2010). Salaisook et al. (2023) highlighted this as a significant issue in the Thai agricultural sector. Moreover, importantly Socio-cultural factors, including the aging population of farmers and their reluctance to change traditional farming practices, also have an important impact on hindering technology adoption. The older generation of farmers is often less inclined to adopt new technologies due to unfamiliarity and perceived complexity (Sayruamyat & Nadee, 2020).

2.3 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) provides a framework to understand the factors influencing technology adoption. It focuses on two primary constructs: perceived usefulness (PU) and perceived ease of use (PEOU). PU reflects the degree to which someone expects a particular technology to positively impact their work effectiveness. Research has indicated that PU is a crucial factor influencing the intention to adopt technology in various contexts, including agriculture (Rezaei-Moghaddam & Salehi, 2010; Ambong & Paulino, 2020). PEOU is described as the degree to which a person thinks a technology will be straightforward to use. The more user-friendly a technology is, the more likely individuals are to embrace it. PEOU has been identified as a critical factor influencing technology adoption among farmers (Rezaei, Kurosh, Salehi, and Saeid, 2010). Several studies have applied TAM to understand technology adoption in the Thai agricultural context. Sayruamyat and Nadee (2020) used TAM to evaluate the intention to use the application among Thai farmers. They found that attitudes toward using the application, perceived usefulness, and perceived ease of use influenced the intention to use the application. Srinuan and Seangnoree (2014) applied TAM to study ICT adoption among rubber smallholders in Southern Thailand. Their findings emphasized the importance of perceived usefulness and ease of use in driving technology adoption. Chaveesuk et al. (2020) extended the TAM framework to understand stakeholders' needs for using blockchain-based smart contracts in the Thai construction industry, which has implications for agribusiness and supply chain management in agriculture. Moreover, recent studies have highlighted emerging trends in agricultural technology adoption. Quang Doan et al. (2024) explored how the social and economic environment influences farmers' decisions to sell products online in Vietnam, which could be relevant for Thai farmers considering similar technologies. Cavite et al. (2023) investigated farmers' perceptions of consumer information and adoption intention towards natural rice cultivation in Thailand, emphasizing the role of community enterprises in technology adoption. Thomas et al. (2023) conducted a systematic review of empirical research on technology acceptance in smart agriculture, providing a comprehensive overview of factors influencing adoption across various contexts.

2.4 Conclusion

The literature reveals that obstacles to technology adoption in the Thai agricultural sector are multifaceted, involving knowledge, skills, infrastructure, financial constraints, and socio-cultural factors. The Technology Acceptance Model (TAM) offers a comprehensive framework for analyzing these challenges, emphasizing perceived usefulness and perceived ease of use as crucial factors in technology adoption.

Addressing these obstacles through targeted interventions, training programs, and policy reforms is essential to enhance the adoption of modern agricultural technologies in Thailand. Future research should focus on exploring the interplay between these factors and developing strategies to overcome adoption obstacles in the specific context of Thai agriculture.

CHAPTER III
RESEARCH METHODOLOGY

3.1 Conceptual Framework

The research aims to investigate the factors influencing agricultural technology adoption among Thai farmers, using the Technology Acceptance Model (TAM) to identify challenges and opportunities for enhancing adoption rates.

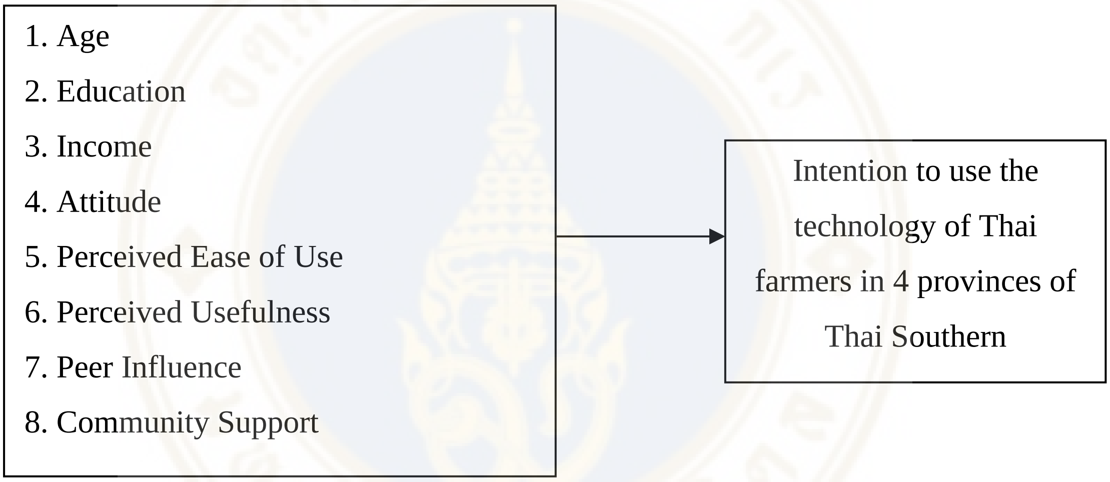

Figure 3.1 Conceptual Framework

This section outlines the research methodology used to investigate the obstacles to technology adoption in the Thai agricultural sector, specifically among farmers growing rubber plants, fruit plants, and other crops in southern Thailand.

3.2 Research Approach

The research employs numerical methods, gathering data through a standardized questionnaire as the primary data collection method. The quantitative approach is suitable for examining the relationships between factors identified in the study's conceptual outline and the validation of hypotheses concerning farmers' technological adaptation. This method facilitates the gathering of extensive data, offering the statistical strength required to detect important patterns and trends.

The survey method is particularly appropriate for this study as it enables the gathering of detailed information on farmers' perceptions, attitudes, and behaviors regarding agricultural technology adoption. The survey was designed to capture data on the key constructs of the TAM framework, as well as demographic and contextual factors that might influence technology adoption.

3.3 Data Collection Methods

The primary data for this study was collected through a structured survey, which was administered to a sample of farmers in Southern Thailand. The survey instrument was designed to measure the constructs of the Technology Acceptance Model (TAM), along with additional variables that could influence technology adoption.

3.3.1 Survey

The survey instrument consisted of several sections, each targeting different aspects of technology adoption:

- Demographics: This section collected data on the respondents' age, gender, education level, income, type of crops grown, and farm size.
- Technology Usage: Respondents were asked about their current use of various technologies, including smartphones, tablets, laptops, and desktop computers, as well as specific agricultural technologies such as precision farming tools, mobile apps, and automated irrigation systems.
- TAM Constructs: The core section of the survey focused on measuring Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Behavioral Intention (BI) to adopt new technologies. Respondents used a five-tier scale to convey their agreement levels, with the lowest score (1) representing strong disagreement and the highest (5) denoting strong agreement.
- Social Influence and Support: Questions in this section assessed the impact of peer influence and community support on the respondents' intention to adopt new technologies.

- Obstacles to Adoption: This section explored potential obstacles to technology adoption, such as lack of technical knowledge, financial constraints, and infrastructural limitations.

3.4 Sampling method

3.4.1 Participant Selection

Participants for this study are carefully chosen to ensure that the insights gathered are highly relevant and representative of the target population. The selection process was guided by two key questions designed to filter participants based on their direct involvement in agriculture within the southern provinces of Phatthalung, Songkhla, Trang, and Nakhon Si Thammarat. Through this rigorous selection process, only those participants who met both criteria were included in the research. This deliberate focus ensures that the data collected is geographically relevant and deeply reflective of the local agricultural sector's realities.

3.4.2 Survey Distribution.

The survey targeted farmers in Nakhon Sri Thammarat, Phatthalung, Trang, and Songkhla who grow rubber plants, fruit, and other crops. A stratified random sampling technique ensured diverse representation from regional provinces. The final sample included responses from 193 farm households, providing a robust dataset for analysis.

3.5 Quantitative Methods

The study uses a quantitative approach to explore the factors affecting the adoption of agricultural technologies in the southern Thai provinces of Nakhon Si Thammarat, Trang, Phatthalung, and Songkhla. Data is collected through an online survey using Google Forms, focusing on farmers' views, attitudes, and behaviors regarding technology use. Out of the 210 responses received, 193 met the screening criteria, ensuring that only participants directly involved in agriculture within the targeted areas were included.

The survey was structured into sections covering screening questions, demographic information, and technology possession. It also included questions on Perceived Usefulness (PU) and Perceived Ease Of Use (PEOU), both measured using Likert scales. Additionally, the survey assessed participants' readiness and attitude toward adopting new technologies, their need for training and support, the types of technologies currently used, and any obstacles they face, along with suggestions for improvement. The Likert scale questions provide insights into how participants feel about these topics, making it easier to analyze the key factors influencing technology adoption in the region.

3.6 Data Analysis

The data collected from the survey was systematically evaluated through a combination of descriptive statistics and inferential statistical techniques. The analysis aimed to identify the relationships between the TAM constructs (PU, PEOU, and BI) and the actual use of agricultural technologies, as well as to explore the impact of demographic variables and social influences on technology adoption.

3.7 Descriptive Analysis

The data were synthesized from survey responses through various statistical methods, including arithmetic means, median values, count tabulations, and ratio analyses. This process illuminated respondent characteristics, technology usage patterns, and perceptions of technology. This initial analysis helped to identify general trends and patterns in the data.

3.8 Inferential Analysis

To test the hypotheses related to the Technology Acceptance Model, the following inferential statistical techniques were applied:

- Correlation Analysis: The study employed linear correlation analysis to gauge the intensity and orientation of connections between the main TAM constructs (PU and PEOU) and intention to use.

- Multiple Regression Analysis: Multiple regression analysis was used to evaluate the combined influence of perceived usefulness, perceived ease of use, and other demographic factors on behavioral intention. This approach helped identify the relative importance of each factor in predicting farmers' willingness to adopt new technologies.

3.9 Handling Missing Data

In cases where survey responses were incomplete, missing data were handled using multiple imputation methods to preserve the integrity of the dataset. This approach ensured that the analysis remained robust and that the results were not biased by missing data.

3.10 Software Tools

The data analysis was conducted using statistical software packages such as Jamovi for analysis. These tools provided the necessary functionality to perform both descriptive and inferential analyses and to generate visual representations of the data, such as charts and graphs.

CHAPTER IV
DATA ANALYSIS

4.1 Frequencies Statistics

4.1.1 Demographics

Table 4.1 Frequency Test of Gender

Age	Counts	% of Total	Cumulative %
< 30 years	16	8.30%	8.30%
31-40 years	61	31.60%	39.90%
41-50 years	65	33.70%	73.60%
51-60 years	38	19.70%	93.30%
> 60 years	13	6.70%	100.00%

The sample population shows a concentration in middle-age groups. The largest age group is 41-50 years, comprising 33.7% of the total, closely followed by the 31-40 years group at 31.6%. Together, these two groups account for 65.3% of the population. The 51-60 years category represents 19.7% of the sample. Younger individuals (under 30) and older individuals (over 60) are less represented, making up 8.3% and 6.7% respectively. Cumulatively, 73.6% of the population is 50 years old or younger, while 93.3% is 60 years old or younger. This age distribution suggests a workforce or population that skews towards middle age, with smaller representations at both younger and older ends of the spectrum.

Table 4.2 Frequency Test of Education

Education	Counts	% of Total	Cumulative %
Bachelor's degree	122	63.20%	63.20%
High school	30	15.50%	78.80%
Postgraduate or Higher Degree	23	11.90%	90.70%
Primary education	2	1.00%	91.70%
Vocational education	13	6.70%	98.40%
Secondary education	3	1.60%	100.00%

The survey sample (N=193) shows a predominantly high level of education among respondents. The majority (63.2%) hold a bachelor's degree, while additional 11.9% have postgraduate or higher degrees. This means that 75.1% of the sample has at least a bachelor's level education. High school graduates make up 15.5% of respondents, followed by those with vocational education at 6.7%. Only a small fraction of the sample has secondary (1.6%) or primary (1.0%) education as their highest level. This education distribution indicates a well-educated sample, which may affect agricultural technology adoption. The high proportion of respondents with tertiary education suggests that the findings may be more representative of farmers with advanced formal education. This could potentially influence technology acceptance and understanding positively. However, the underrepresentation of those with lower education levels should be considered when generalizing the results to the broader farming population.

Table 4.3 Frequency Test of Province

Province	Counts	% of Total	Cumulative %
Nakhon Sri Thammarat	34	17.60%	17.60%
Phatthalung	120	62.20%	79.80%
Songkhla	16	8.30%	88.10%
Trang	23	11.90%	100.00%

The data shows the distribution across four provinces, Phatthalung dominates the sample, accounting for 62.2% (120 counts) of the total. Nakhon Sri Thammarat is the second most represented, with 17.6% (34 counts). Trang follows with 11.9% (23 counts).

Songkhla has the smallest representation at 8.3% (16 counts). Notably, Phatthalung alone represents nearly two-thirds of the entire sample. The cumulative percentage indicates that Phatthalung and Nakhon Sri Thammarat together account for 79.8% of the data. This distribution suggests a significant concentration in Phatthalung, with considerably smaller representations from the other three provinces. The data may reflect population distribution, survey responses, or another measured variable across these regions.

4.1.2 Technology possession

Table 4.4 Frequencies of Smart Phone Owner

Smart Phone Owner	Counts	% of Total	Cumulative %
No	9	4.7 %	4.7 %
Yes	184	95.3 %	100.0 %

The result reveals a striking prevalence of smartphone ownership among the surveyed population. Out of 193 total respondents, an overwhelming 184 (95.3%) own smartphones, while only 9 (4.7%) do not. This exceptionally high ownership rate suggests a technologically savvy group, where smartphones are nearly ubiquitous.

Table 4.5 Frequencies of Tablet Owner

Tablet Owner	Counts	% of Total	Cumulative %
No	91	47.2 %	47.2 %
Yes	102	52.8 %	100.0 %

The result reveals a nearly even split in tablet ownership among the 193 respondents. Slightly over half (52.8% or 102 individuals) own tablets, while 47.2% (91 individuals) do not. This close distribution suggests that tablets are popular but not ubiquitous in this population. The 52.8% tablet ownership rate contrasts significantly with previously reported 95.3% smartphone ownership, indicating that while tablets are common, they haven't reached the same level of adoption as smartphones.

Table 4.6 Frequencies of Laptop Owner

Laptop Owner	Counts	% of Total	Cumulative %
No	107	55.4 %	55.4 %
Yes	86	44.6 %	44.6 %

The result shows a slight majority of non-laptop owners among the 193 respondents. 55.4% (107 individuals) do not own laptops, while 44.6% (86 individuals) do. This distribution reveals that laptops are less common than both smartphones (95.3% ownership) and tablets (52.8% ownership) in this population. The relatively close split suggests a significant presence of laptops, but also indicates a trend towards mobile device preference. Laptop ownership being lower than both smartphones and tablets implies that mobile devices may be meeting many computing needs for this group.

4.1.3 Social media usage

Table 4.7 Frequencies of Social Media Applications

Social media applications	Counts	% of Total	Cumulative %
Facebook	2	1.0 %	1.0 %
Facebook, Instagram	1	0.5 %	1.6 %
Facebook, Instagram, WhatsApp	2	1.0 %	2.6 %
Facebook, Line	62	32.1 %	34.7 %
Facebook, Line, Instagram	40	20.7 %	55.4 %
Facebook, Line, Instagram, WhatsApp	2	1.0 %	56.5 %
Facebook, Line, WhatsApp	2	1.0 %	57.5 %
Facebook, Line, X (Twitter)	20	10.4 %	67.9 %
Facebook, Line, X (Twitter), Instagram	22	11.4 %	79.3 %
Facebook, Line, X (Twitter), Instagram, WhatsApp	2	1.0 %	80.3 %
Facebook, Line, X (Twitter), WhatsApp	1	0.5 %	80.8 %
Facebook, X (Twitter)	3	1.6 %	82.4 %
Facebook, X (Twitter), Instagram	18	9.3 %	91.7 %
Facebook, X (Twitter), Instagram, WhatsApp	1	0.5 %	92.2 %
Facebook, X (Twitter), WhatsApp	1	0.5 %	92.7 %

Table 4.7 Frequencies of Social Media Applications (cont.)

Social media applications	Counts	% of Total	Cumulative %
Line	7	3.6 %	96.4 %
Line, Instagram	1	0.5 %	96.9 %
Line, X (Twitter)	1	0.5 %	97.4 %
Line, X (Twitter), Instagram	3	1.6 %	99.0 %
X (Twitter)	1	0.5 %	99.5 %
X (Twitter), Instagram	1	0.5 %	100.0 %

The data reveals a strong preference for multi-platform social media use among the 193 respondents. Facebook dominates, appearing in 18 out of 21 combinations, followed by Line. Instagram and X (Twitter) are also popular, while WhatsApp is less common. The most prevalent combination is "Facebook, Line" (32.1%), followed by "Facebook, Line, Instagram" (20.7%). Notably, 94.3% of respondents use multiple platforms, indicating diverse social media habits. Facebook and Line often appear together, suggesting complementary roles. The top 10 combinations account for 80.3% of respondents, while several less common combinations exist, highlighting varied usage patterns. This multi-platform preference and the dominance of Facebook and Line have significant implications for social media marketing and communication strategies in this population.

4.2 Factor Analysis

4.2.1 Barlett's test of Sphericity

Table 4.8 Barlett's test of Sphericity

X^2	df	p
1718	105	< .001

The Bartlett's Test of Sphericity result demonstrates a chi-square value of 1718, with 105 degrees of freedom and p-value of < .001. This highly significant result (p < .001) strongly refutes the assumption that the correlation matrix is equivalent to an identity matrix. It indicates that there are significant interrelationships among the variables in the dataset. Therefore, the data is appropriate for factor analysis or other dimension reduction techniques. This result supports proceeding with further analyses to explore the underlying structure of the data.

4.2.2 KMO Measure of Sampling Adequacy (MSA)

Table 4.9 **KMO Measure of Sampling Adequacy (MSA)**

	MSA
Overall	0.911
12. Increased Productivity	0.889
13. Efficiency	0.889
14. Better Decision Making	0.909
15. Ease of Learning	0.844
16. Ease of Use	0.866
17. Effort Required	0.863
18. Positive Attitude	0.924
19. Beneficial	0.92
20. Satisfaction	0.935
21. Peer Influence	0.951
22. Community Influence	0.948
23. Family Influence	0.942
24. Tangible Benefits	0.93
25. Observation Result	0.913
11. Increase Production	0.897

The overall KMO value of 0.911 indicates excellent sampling adequacy for factor analysis. All individual items show KMO values above 0.8, ranging from 0.844 to 0.951, which are considered very good to excellent. Social factors (peer, community, and family influence) have the highest KMO values. These results suggest that the sample size is sufficient and highly suitable for factor analysis or principal component analysis. This can confidently proceed with further analyses to explore the underlying structure of the data.

4.2.3 Eigenvalue

Table 4.10 Initial Eigenvalues

Component	Eigenvalue	% of Variance	Cumulative %
1	7.295	48.64	48.6
2	1.758	11.72	60.4
3	1.1	7.34	67.7
4	0.667	4.45	72.1
5	0.624	4.16	76.3
6	0.595	3.97	80.3
7	0.513	3.42	83.7
8	0.473	3.15	86.8
9	0.391	2.6	89.4
10	0.358	2.39	91.8
11	0.312	2.08	93.9
12	0.252	1.68	95.6
13	0.247	1.65	97.2
14	0.224	1.49	98.7
15	0.189	1.26	100

The shows the results of the eigenvalues and the variance each component explains, the results of the first three components have eigenvalues greater than 1, which indicates they are significant. Together, they explain 67.7% of the total variance, with the first component alone accounting for 48.64%. This suggests that focusing on these three components is sufficient to capture most of the important information in the dataset while simplifying the analysis.

4.2.4 Principal Component Analysis (PCA)

Table 4.11 Principal Component Analysis (PCA)

Component Loadings	Component			
	1	2	3	Uniqueness
25. Observation Result	0.886			0.250
24. Tangible Benefits	0.785			0.315
23. Family influence.	0.715			0.401
21. Peer influence	0.703			0.367
22. Community Influence	0.697			0.453
20. Satisfaction	0.669			0.380
18. Positive Attitude	0.612			0.331
19. Beneficial	0.609			0.323
13. Efficiency		0.845		0.231
14. Better Decision Making		0.839		0.229
12. Increased Productivity		0.783		0.263
11. Increase production		0.758		0.336
16. Ease of Use			0.821	0.244
17. Effort Required			0.740	0.423
15. Ease of Learning			0.727	0.298

The demonstrates of a Principal Component Analysis (PCA) with oblimin rotation, showing component loadings for three factors. The analysis aimed to identify the underlying dimensions influencing farmers' adoption of agricultural technology. Factor analysis revealed a three-component structure: Component 1 Attitudinal factors (e.g., observation results, benefits, and social influences), Component 2 represents Perceived usefulness (e.g., decision-making and increased productivity), and Component 3 reflects Perceived ease of use (e.g., the effort required and ease of learning). All items showed strong loadings (>0.6) on their respective components with low uniqueness values (<0.5), indicating a robust factor structure that aligns well with key constructs in technology acceptance models.

4.3 Regression Analysis

4.3.1 Attitude to use

Table 4.12 Model Fit Measures – Attitude to Use

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1	0.746	0.556	0.549	78.9	3	189	< .001

Note. Models estimated using sample size of N=193

This displays the overall model fit. The R value of 0.746 a robust positive association between the independent and outcome variables. The R^2 value of 0.556 indicates that the predictive model accounts for 55.6% of the variability in this response variable. The adjusted R^2 of 0.549, being close to the R^2, shows that the model is not overfitted. The overall model test yields an F-statistic of 78.9 with 3 and 189 degrees of freedom, and the p-value < 0.001 confirms that the model is statistically significant.

Table 4.13 Omnibus ANOVA Test – Attitude to Use

	Sum of Squares	**df**	**Mean Square**	**F**	**p**
Attitude	25.562	1	25.562	74.78	< .001
Perceived Usefulness	3.630	1	3.630	10.62	0.001
Perceived Ease of Use	0.799	1	0.799	2.34	0.128
Residuals	64.610	189	0.342		

To explain the variance by each predictor of the Omnibus ANOVA test. Attitude has the highest sum of squares (25.562) and F-value (74.78), with p < 0.001, indicating it's the most significant predictor, while other two predictors such Perceived Usefulness is also significant (F = 10.62, p = 0.001) and Perceived Ease of Use is failed to reach statistical significance in the study (F = 2.34, p = 0.128). The residuals (unexplained variance) have a sum of squares of 64.610.

Table 4.14 Model Coefficients – Attitude to Use

Predictor	Estimate	SE	t	p
Intercept	-0.0738	0.3030	-0.244	0.808
Attitude	0.8453	0.0978	8.647	< .001
Perceived Usefulness	0.2890	0.0887	3.259	0.001
Perceived Ease of Use	-0.1072	0.0702	-1.529	0.128

This shows the individual predictor effects: The intercept is not significantly different from 0 (p = 0.808). Attitude has the strongest positive effect (estimate = 0.8453, p < 0.001), while Perceived Usefulness has a moderate positive effect (estimate = 0.2890, p = 0.001). However, Perceived Ease of Use has a slight negative effect, but it's not statistically significant (estimate = -0.1072, p = 0.128). In summary, the result explains a substantial portion of the variation in attitude to use. Attitude and Perceived Usefulness are significant predictors, while Perceived Ease of Use doesn't contribute significantly to the model.

4.3.2 Likelihood of Adoption

Table 4.15 Model Fit Measures – Likelihood of Adoption

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1	0.691	0.477	0.469	57.4	3	189	< .001

Note. Models estimated using sample size of N=193

The result has an R value of 0.691, indicating a moderately strong correlation between the predictors and the likelihood of adoption. The R^2 is 0.477, meaning the result explains 47.7% of the variance in the likelihood of adoption. The adjusted R^2 (0.469) is close to R^2, suggesting the model isn't overfitted. The overall model is statistically significant (F = 57.4, df1 = 3, df2 = 189, $p < 0.001$), indicating that the predictors collectively have a significant effect on the likelihood of adoption.

Table 4.16 Omnibus ANOVA test – Likelihood of Adoption

	Sum of Squares	df	Mean Square	F	p
Attitude	0.191	1	0.191	0.497	0.482
Perceived Usefulness	31.766	1	31.766	82.772	< .001
Perceived Ease of Use	2.177	1	2.177	5.673	0.018
Residuals	72.534	189	0.384		
Note. Type 3 sum of squares					

This breaks down the contribution of each predictor, Perceived Usefulness is the most significant predictor (F = 82.772, $p < 0.001$), while Perceived Ease of Use is also significant (F = 5.673, p = 0.018). In contrast, surprisingly, Attitude is not statistically significant (F = 0.497, p = 0.482).

Table 4.17 Model Coefficient – Likelihood of Adoption

Predictor	Estimate	SE	t	p
Intercept	-0.0307	0.3210	-0.0955	0.924
Attitude	-0.0730	0.1036	-0.7048	0.482
Perceived Usefulness	0.8549	0.0940	9.0979	< .001
Perceived Ease of Use	0.1770	0.0743	2.3819	0.018

The model coefficients show the intercept is not significantly different from zero (p = 0.924). Perceived Usefulness has the strongest positive effect because the estimate value is 0.8549 and P-value is less than 0.001, while Perceived Ease of Use has a moderate positive effect because estimate value is equal to 0.1770 and P-value is equal to 0.018. However, Attitude has a slight negative effect, it's not statistically significant due to estimate is equal to -0.0730 and P-value is 0.482. Therefore, this model explains a moderate amount of variance in the likelihood of adoption. Perceived Usefulness is the strongest predictor, followed by Perceived Ease of Use. Interestingly, Attitude doesn't significantly contribute to predicting the likelihood of adoption in this model, which is unexpected given its typical importance in technology adoption theories. This suggests that for this particular technology or context, practical considerations (Usefulness and simplicity of use) will be more important than general attitudes in determining adoption likelihood.

4.3.3 Increase of Production

Table 4.18 Model Fit Measures for Increase of Production

				Overall Model Test			
Model	**R**	**R^2**	**Adjusted R^2**	**F**	**df1**	**df2**	**p**
1	0.800	0.640	0.634	112	3	189	< .001

Note. Models estimated using sample size of N=193

This result reveals a robust model fit, with an R value of 0.800, indicating a high correlation between the predictors and the increase in production. The R^2 of 0.640 indicates, 64% of the variation in production increase can be accounted by the model. The adjusted R^2 of 0.634, being close to the R^2, indicates that the model is not overfitted. The overall result is highly significant ($F = 112$, $df1 = 3$, $df2 = 189$, $p < 0.001$), indicating that the predictors collectively have a strong effect on the increase of production.

Table 4.19 Omnibus ANOVA test for Increase of Production

	Sum of Squares	df	Mean Square	F	p
Attitude	0.201	1	0.201	0.806	0.370
Perceived Usefulness	43.492	1	43.492	174.263	< .001
Perceived Ease of Use	1.127	1	1.127	4.516	0.035
Residuals	47.170	189	0.250		

Note. Type 3 sum of squares

These findings from Omnibus ANOVA test mean;

1. Perceived Usefulness is the strongest predictor of increased production. The highest F-value is equal to 174.263 while the p-value is showing extremely low as < 0 .001. They show that perceived usefulness has a strongly significant impact on

production increase. This suggests that when users see the technology as useful, it's strongly associated with increased production.

2. Perceived Ease of Use is not as strong as Perceived Usefulness, this is still a significant predictor because the F-value of 4.516 and p-value of .035 (which is < .05) presenting the ease of use has a statistically significant impact on production increase. This implies that making the technology easier to use is associated with some increase in production, though not as strongly as its perceived usefulness.

3. Attitude is an interesting finding, as it suggests that general attitudes towards the technology don't significantly impact its ability to increase production because the F-value of 0.806 and p-value of .370 (which is > .05) are not a statistically significant predictor of production increase.

These results indicate that to boost production, efforts should focus primarily on enhancing and demonstrating the usefulness of the technology, followed by improving its ease of use. Surprisingly, attempting to change general attitudes towards the technology may not be an effective strategy for increasing production in this context.

Table 4.20 Model Coefficients for Increase of Production

Predictor	Estimate	SE	T	p
Intercept	-0.0406	0.2589	-0.157	0.876
Attitude	-0.0750	0.0835	-0.898	0.370
Perceived Usefulness	1.0003	0.0758	13.201	< .001
Perceived Ease of Use	0.1274	0.0599	2.125	0.035

The Model Coefficients of Increase production are showing

Firstly, the intercept is not significantly different from zero (p = .876). This means that when all other variables are zero, the expected value of Increase production is not significantly different from zero. In practical terms, this suggests that without the influence of the other factors, there's no significant baseline increase in production.

Secondly, Prceived Usefulness has a very strong positive effect (estimate = 1.0003, p < .001). The coefficient is approximately 1, which means that for every one-unit increase in Perceived Usefulness, there's about a one-unit increase in production.

This relationship is highly statistically significant (p < .001), indicating strong evidence against the null hypothesis of no effect.

Thirdly, Perceived Ease of Use has a moderate positive effect (estimate = 0.1274, p = .035). For each one-unit increase in Perceived Ease of Use, there's an expected increase of about 0.1274 units in production. This relationship is statistically significant at the 0.05 threshold, providing evidence that Perceived Ease of Use does have a real effect on increasing production.

Fourthly, Attitude shows a slight negative effect (estimate = -0.0750), but it's not statistically significant (p = .370). We can't conclude that Attitude has a real effect on production increase based on this data, as the observed negative relationship could be due to random chance. In summary, this model explains a substantial amount (64%) of the variance in the increase of production. Perceived Usefulness is the strongest predictor by a large margin, suggesting that the utility of the technology is the primary driver of increased production. Perceived Ease of Use also contributes positively, though to a lesser extent. Interestingly, Attitude does not significantly impact the increase in production, indicating that practical considerations (usefulness and ease of use) are more important than general attitudes in determining productivity gains.

Therefore, the results suggest that to drive increases in production, focusing on improving and communicating the usefulness of the technology, as well as ensuring it's easy to use, would be more effective than trying to change general attitudes towards it.

4.4 Cross Tabulation Analysis

4.4.1 Desirable to use vs Income

This shows the relationship between income levels and the desirability to use a certain agricultural technology.

Table 4.21 The relationship between income levels and the desirability to use a certain agricultural technology

30. Desirable to Use	< 5,000 baht	5,001 - 10,000 baht	10,001 - 20,000 baht	20,001 - 30,000 baht	> 30,000 baht	Total
Strongly Disagree to Use	1	0	1	0	0	2
Disagree to Use	1	4	0	0	0	5
Neutral to Use	10	14	18	9	3	54
Agree to Use	10	36	29	10	1	93
Strongly Agree to Use	7	15	6	10	1	39
Total	**29**	**69**	**61**	**29**	**5**	**193**

The contingency analysis of income versus desirability to use reveals interesting patterns in consumer attitudes. The majority of respondents are concentrated in the lower to middle-income brackets, with the 5,001-10,000 baht range attracting the highest number of participants (69), closely followed by the 10,001-20,000 baht (61). This distribution suggests that the product or service in question primarily appeals to or is targeted at individuals in these income categories.

Across all income levels, there is a clear trend towards a positive reception, with "Agree to use" being the most frequent response (93). This indicates a generally favorable attitude towards the product or service regardless of income. However, the data also shows some nuances. The highest income bracket (>30,000 baht) has notably fewer respondents, which could imply either a smaller sample size in this category or potentially less interest from higher earners.

Interestingly, the lowest income group (<5,000 baht) displays a more balanced distribution of responses across the desirability spectrum. This suggests that individuals in this income bracket have more varied opinions about the product or service, possibly due to factors such as affordability concerns or diverse needs within this economic group.

Overall, while there's a general inclination towards agreement across income levels, the varying response patterns among different income brackets highlight the importance of considering economic factors in product development and marketing strategies.

4.4.2 Desirable to use vs Age

This presents the relationship between age groups and the desirability to use a certain agricultural technology.

Table 4.22 The relationship between age groups and the desirability to use a certain agricultural technology

30. Desirable to Use	< 30 years	31-40 years	41-50 years	51-60 years	> 60 years	Total
Strongly Disagree to Use	1	0	1	0	0	2
Disagree to Use	1	0	2	2	0	5
Neutral to Use	7	20	14	12	1	54
Agree to Use	3	33	38	13	6	93
Strongly Agree to Use	4	8	10	11	6	39
Total	**16**	**61**	**65**	**38**	**13**	**193**

The age-based contingency reveals significant insights into the desirability of use across different generations. The 41-50 years age group emerges as the most represented demographic, with 65 respondents, suggesting strong engagement or interest from this middle-aged cohort. Across all age categories, "Agree to use" stands out as the predominant response, totally 193 participants. This indicates a generally positive reception of the product or service regardless of age.

Notably, the 31-40 and 41-50 age groups demonstrate the highest levels of agreement to use, pointing to a particular appeal or relevance to individuals in their 30s and 40s. In contrast, the youngest (<30 years) and oldest (>60 years) age brackets have fewer respondents overall, which could reflect either sampling limitations or potentially less interest from these age groups.

Interestingly, neutral responses are distributed fairly evenly across most age categories, with the exception of the over-60 group. This suggests that while most age groups include a consistent proportion of undecided individuals, the oldest demographic may have more polarized opinions.

These patterns highlight the importance of age-specific considerations in product development and marketing strategies, particularly focusing on the preferences and needs of the 31-50 age range, while potentially exploring ways to increase appeal to younger and older demographics.

4.4.3 Desirable to use vs Education

This presents the relationship between Education groups and the desirability to use a certain agricultural technology.

Table 4.23 The relationship between education groups and the desirability to use a certain agricultural technology

30. Desirable to Use	Primary Education	Secondary Education	High School	Vocational Education	Bachelor's Degree	Postgraduate or Higher Degree	Total
Strongly Disagree to Use	0	0	1	0	1	0	2
Disagree to Use	0	0	2	0	2	1	5
Neutral to Use	2	1	12	5	30	4	54
Agree to Use	0	0	10	7	66	10	93
Strongly Agree to Use	0	2	5	1	23	8	39
Total	**2**	**3**	**30**	**13**	**122**	**23**	**193**

The contingency examining education levels and desirability to use reveals significant trends in consumer attitudes. Bachelor's degree holders dominate the sample, comprising 122 of the 193 total respondents. This large representation suggests that the product or service may be particularly relevant or appealing to individuals with higher education.

Across all education levels, "Agree to use" emerges as the most common response, with 93 total respondents indicating a generally positive reception. Notably, those with higher education levels, specifically Bachelor's and Postgraduate degrees, demonstrate a stronger inclination to agree to use the product or service. This trend implies that increased education may correlate with greater appreciation or perceived value of the offering.

The data shows very few respondents with only primary or secondary education, which could reflect either sampling limitations or potentially less engagement from these groups. Interestingly, individuals with vocational education display a more balanced distribution of responses across the desirability spectrum, suggesting diverse opinions within this educational category.

These patterns underscore the importance of considering educational background in product development and marketing strategies, with a potential focus on appealing to and addressing the needs of those with higher education levels, while also exploring ways to engage individuals across the entire educational spectrum.

CHAPTER V
CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The adoption of agricultural technology among farmers in southern Thailand involves a complex interaction of demographic, technological, and psychological factors. This study explores these dynamics, offering insights into how farmers accept and integrate technology, as well as the potential impact of such adoption on agricultural productivity in the region.

The demographic data from the study indicates that the majority of the farming population is middle-aged, with most farmers falling between the ages of 31 and 50. This age group combines the experience of traditional farming with a willingness to embrace innovation, suggesting that these farmers may be particularly receptive to new agricultural technologies. In addition, the educational background of the respondents shows a notrend towards higher education, with more than three-quarters of participants holding at least a bachelor’s degree. This level of formal education is likely to enhance the farmers' ability to understand and adopt new technologies, contributing to higher technology uptake in the region.

Regarding technology ownership, the study reveals a strong preference for mobile devices, especially smartphones. The fact that 95.3% of the surveyed farmers own smartphones highlights the extent to which digital technology is already integrated into their daily lives. This widespread smartphone ownership presents a valuable opportunity for the development of mobile-based agricultural tools. While tablet ownership is somewhat moderate and laptop ownership lower still, the overall trend towards mobile technology emphasizes the importance of adopting a mobile-first strategy when developing agricultural technologies for this group.

The study also examines the social media usage habits of the farmers, underscoring the role of digital platforms in their lives. A large majority of the farmers use multiple social media applications, with Facebook and Line being the most commonly used platforms. This engagement with digital platforms suggests that farmers are well-connected to online information sources and networks. These platforms can be effectively leveraged to disseminate agricultural information, offer technical support, and promote community interaction around new farming technologies.

In exploring the factors that influence technology adoption, the study identifies three primary components through factor analysis: attitudinal factors, perceived usefulness, and perceived ease of use. All three components align closely with established models of technology acceptance and provide a framework for understanding the decision-making process farmers undergo when considering the adoption of new agricultural technologies.

Regression analysis provides further detail on the significance of these factors. While attitudinal factors and perceived usefulness both play an important role in shaping farmers' attitudes toward using new technologies, the key predictors of actual adoption are perceived usefulness and perceived ease of use. This finding indicates that while positive attitudes toward technology are important, practical considerations—such as the utility and user-friendliness of the technology—are more critical when it comes to actual adoption decisions.

The analysis further demonstrates that perceived usefulness is the most significant predictor of increased agricultural production. This highlights the necessity of showing farmers clear and tangible benefits, such as increased productivity, when introducing new technologies. Additionally, the finding that perceived ease of use is the second most important predictor underscores the importance of designing technologies that are user-friendly and providing adequate training programs to ensure that farmers can confidently integrate new tools into their operations.

The study also conducted a cross-tabulation analysis across different income levels, age groups, and education levels. The results revealed a generally positive attitude toward technology adoption, though variations were observed across certain groups. For instance, the analysis showed that farmers in the lowest income brackets expressed more varied opinions about adopting technology, indicating that economic considerations play a significant role in technology acceptance. These variations highlight the need for deployment strategies that are mindful of economic constraints and tailored to the specific needs of different income groups.

In conclusion, this study paints a picture of a farming community in southern Thailand that is well-educated, connected to digital technology, and open to innovation. The high rate of smartphone ownership and active social media use create ready-made channels for introducing and supporting new agricultural technologies. However, the success of these technologies will largely depend on their ability to demonstrate clear practical benefits and ease of use to the farmers.

The results of this study offer important insights for policymakers, agricultural technology developers, and extension services. By focusing on the factors that most strongly influence adoption and productivity—particularly perceived usefulness and ease of use—stakeholders can potentially design more potent methods for promoting the adoption of agricultural technologies in the region. Furthermore, the insights gained from the study regarding demographic variations and social media usage patterns can help inform targeted outreach and support programs that address the specific needs of different groups within the farming community.

As the agricultural sector continues to face challenges related to climate change, population growth, and economic pressures, the adoption of innovative technologies will be essential for ensuring food security and improving the livelihoods of farmers. This study offers a foundation for evidence-based strategies to navigate the complexities of technology adoption in southern Thailand, helping to guide the region's agricultural transformation toward a more sustainable and productive future.

5.2 Recommendations

To enhance the adoption of agricultural technologies in southern Thailand, several strategies can be recommended.

Firstly, it is crucial to emphasize the practical benefits and productivity gains of these technologies. The concept of Perceived Usefulness has emerged as a key predictor of both adoption and increased production, indicating that when farmers recognize tangible benefits, they are more likely to embrace new tools and systems. Therefore, any effort to promote agricultural technologies should focus on demonstrating their immediate and measurable advantages in terms of improving yield, reducing costs, or enhancing efficiency. Another important strategy is to improve the ease of use of these technologies. Investing in user-friendly interfaces and providing adequate training programs will help make the technologies more accessible to farmers, many of whom may not have extensive experience with advanced tools. Enhancing Perceived Ease of Use is vital not only for increasing the likelihood of adoption but also for ensuring that the technologies contribute meaningfully to production gains.

Given the high rate of smartphone ownership among farmers in the region, a mobile-first approach should be prioritized. This means that technologies and applications should be designed to function seamlessly on mobile devices, allowing farmers to access and utilize them more conveniently. Mobile compatibility is essential for ensuring widespread use, especially considering that smartphones are the most commonly owned technological devices in rural areas.

A targeted social media strategy is also recommended, utilizing platforms such as Facebook and Line for outreach, education, and support. These platforms are highly popular among farmers and can serve as effective channels for disseminating information, offering technical assistance, and creating communities where farmers can share experiences and learn from one another. The Age-specific engagement is another critical aspect of a successful technology adoption strategy. Tailored outreach and training programs should be designed to address the specific needs of different age groups. In particular, the study showed that farmers aged 31-50 are the most active users of technology, so initial efforts should focus on this group. However, it is equally important to develop strategies for engaging younger farmers and those over 60, as their perspectives and experiences with technology may differ. Moreover, attention should also be paid to education-level considerations. While a large proportion of the study's sample consisted of well-educated farmers, it is important to design educational materials and training programs that are accessible to those with lower levels of formal education. Ensuring that all farmers, regardless of educational background, can benefit from technology is essential for achieving widespread adoption.

However, in terms of regional focus, initial efforts should be concentrated in Phatthalung province, where the majority of the study's respondents were located. This targeted approach will allow stakeholders to refine their strategies before expanding to other regions of Thailand. Starting with a concentrated area ensures that lessons learned from early adopters can inform future efforts in other provinces.

Additionally, peer learning and community engagement should be leveraged the study's results to emphasize the importance of social factors, as peer influence and community support can greatly encourage farmers to adopt new technologies. By promoting peer learning initiatives and fostering community-based support systems, stakeholders can create a positive environment where farmers feel encouraged to try new technologies based on the experiences of those they trust.

To ensure that the adoption of agricultural technologies is both effective and sustainable, it is important to implement a system of continuous assessment. Regularly evaluating the impact of these technologies on productivity and farmer satisfaction will provide valuable feedback for refining and improving the tools offered. This ongoing process of assessment will help ensure that technologies remain relevant and useful to farmers over time.

While the focus of these strategies should be on usefulness and ease of use, it is also important not to neglect attitudinal factors. Although attitudes towards technology may not directly predict adoption, they do influence the broader acceptance of new innovations. Efforts to shift attitudes toward openness and a willingness to experiment with technology can support long-term adoption efforts.

By implementing these recommendations, stakeholders can foster conditions that encourage the adoption of agricultural technologies in southern Thailand. These strategies could boost productivity and enhance farmers' livelihoods, while also supporting the modernization and sustainability of the region's agricultural sector

5.3 Limitations and Suggestion for Future Research

This study provides important perspectives on the adoption of technology in the agricultural sector of southern Thailand, but several limitations should be considered.

The first limitation lies in the geographic scope of the research. The study was primarily conducted in four provinces, with a significant portion of the data collected from Phatthalung province, which accounted for 62.2% of the respondents. As a result, the findings may not fully represent the agricultural practices and challenges faced in other parts of Thailand. Regional differences in agricultural techniques and infrastructural conditions could lead to varying experiences with technology adoption. Thus, the extent to which these conclusions can be broadly applied across various regions warrants careful consideration.

Secondly, the study sample was skewed towards individuals with higher levels of education. A significant 75.1% of the respondents held at least a bachelor's degree, which is not reflective of the broader farming population in Thailand. Many farmers may have lower levels of formal education, and this disparity could influence their familiarity and comfort with adopting new technologies. The educational bias in the sample may have affected the findings, as those with more education are likely to be more adept at using digital tools, thereby limiting the applicability of the study to the entire farming community.

The third limitation concerns the participant's age. The majority of the respondents were between the ages of 31 and 50, accounting for 65.3% of the sample. This focus on middle-aged farmers leaves younger farmers (under 30) and older farmers (over 60) underrepresented. Different age groups may face distinct challenges or have different motivations when it comes to adopting new agricultural technologies. As such, this age imbalance limits the scope of conclusions that can be drawn regarding technology adoption across all generations of farmers.

A fourth limitation is that the study primarily examined general technology ownership, such as smartphones, tablets, and laptops, without delving deeply into specific agricultural technologies. Various technologies, such as precision farming tools or automated irrigation systems, may have different adoption rates and obstacles. By not exploring these in greater depth, the study may not fully capture the complexity of how different types of agricultural technologies are adopted.

Fifth, the research was conducted as a cross-sectional study, providing only a snapshot of technology adoption at one distinct temporal point. This limits the ability to assess how the adoption of technology evolves and how external factors—such as policy changes, economic shifts, or environmental conditions—might influence the rate or manner of adoption in the long term.

Another important limitation is the reliance on self-reported data, which can be subject to biases. Respondents may provide answers they believe are socially acceptable, leading to social desirability bias, or they may not accurately recall their past behavior or attitudes toward technology use. These potential biases could affect the accuracy of the findings.

The seventh limitation is that while the study identified key factors influencing technology adoption, it did not deeply explore the specific obstacles faced by those who exhibited low intention to adopt technology. A more comprehensive investigation into the obstacles encountered by these individuals could provide valuable insights for developing strategies to encourage broader adoption across the farming community.

Finally, the study primarily focused on the intention to use technology and respondents' attitudes toward it, rather than on actual technology adoption and sustained usage patterns. While understanding intentions is important, examining how technology is used in practice would offer a more complete picture of the adoption process and how technologies are integrated into everyday farming practices.

5.3.1 Suggestions for Future Research

To build on the findings of this study and address its limitations, several avenues for future research are recommended.

First, future studies should expand their geographic coverage to include a wider range of regions across Thailand. Conducting comparative studies between different provinces or regions could reveal variations in agricultural practices, infrastructural development, and cultural attitudes that affect technology adoption.

Second, a longitudinal approach would be beneficial in tracking the progression of technology adoption over time. By observing changes in farmers' attitudes and behaviors across different time periods, researchers can gain deeper insights into long-term trends and the sustainability of technology use in agriculture.

Third, future research should aim to include a more balanced representation of educational backgrounds. By encompassing a broader spectrum of education levels, researchers would be able to better understand how varying degrees of formal education influence farmers' ability to adopt new technologies.

Fourth, future studies should target underrepresented age groups, particularly younger and older farmers. Understanding the unique challenges and opportunities that these groups face when adopting technology is crucial for developing interventions that are inclusive and effective across all age demographics.

Fifth, future research should focus on specific agricultural technologies, such as precision farming tools, Internet of Things (IoT) devices, or farm management software. This would allow for a more detailed understanding of the adoption patterns of these particular technologies and their specific impact on agricultural productivity.

Sixth, integrating qualitative research methods, such as in-depth interviews or focus groups, could enhance the quantitative data by offering deeper insights into farmers' decision-making processes. These approaches would provide a better understanding of the contextual factors affecting technology adoption.

Seventh, it would be valuable for future research to go beyond measuring intentions to adopt technology and instead focus on actual usage patterns. Tracking how farmers use technology in their daily operations would help to identify the factors that contribute to the sustained adoption and successful integration of these tools into farming practices.

Moreover, comparative studies between early adopters and those who are slower to adopt or have not adopted new technologies could highlight the key differences that influence these decisions. Such studies could help identify effective interventions to encourage broader technology uptake.

Additionally, assessing the impact of government policies, subsidies, and support programs on technology adoption rates would provide valuable insights into which policy measures are most effective in promoting technology use among farmers. Understanding the economic implications of adopting new agricultural technologies, including the cost-benefit ratio, would also be essential for helping farmers make informed decisions about investing in these tools.

Finally, future research should explore the role of cultural factors, such as traditional farming practices and local knowledge systems, in shaping farmers' decisions to adopt new technologies. By aligning technological advancements with these cultural values, it may be possible to facilitate greater acceptance and integration. Additionally, future studies should investigate how the adoption of new agricultural technologies impacts environmental sustainability. This is particularly important in understanding how technology can help farmers adapt to climate change while maintaining ecological balance.

By addressing these limitations and pursuing the suggested avenues for research, future studies can provide a more comprehensive understanding of technology adoption in the agricultural sector of Thailand. This, in turn, will support the development of more effective strategies to enhance the adoption of technology, improve agricultural productivity, and ultimately benefit the livelihoods of farmers across the country.

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APPENDIX

Appendix A: Questionnaires

แบบสอบถามเกี่ยวกับ ปัจจัยที่มีอิทธิพลการนำเทคโนโลยีมาใช้ในภาคเกษตรกรรมของไทยและการบูรณาการเข้ากับโมเดลการยอมรับเทคโนโลยี

แบบสอบถามนี้เป็นส่วนหนึ่งของการศึกษาค้นคว้าอิสระโดยมีวัตถุประสงค์เพื่อศึกษาเกี่ยวกับปัจจัยที่มี

อิทธิพลการนำเทคโนโลยีมาใช้ในภาคเกษตรกรรมพื้นที่ภาคใต้ของไทยและการบูรณาการเข้ากับโมเดลการยอมรับเทคโนโลยี

ข้อมูลที่รวบรวมผ่านแบบสำรวจนี้จะถูกนำไปใช้เพื่อการศึกษาในหัวข้อดังกล่าวเท่านั้น และจะไม่ถูกนำไปเผยแพร่ที่อื่นแต่อย่างใด คำตอบของท่านจากแบบสำรวจนี้จะสามารถต่อยอดความรู้ และเพิ่มพูนข้อมูลเพิ่มเติมสำหรับงานวิจัยหัวข้อนี้ต่อไปในภายหน้าได้เป็นอย่างดี

ทั้งนี้แบบสำรวจจะใช้เวลาโดยเฉลี่ยไม่เกิน 5 นาที โดยแบ่งชุดคำถามออกเป็น 12 ส่วน ขอความกรุณาทุกท่านตอบแบบสอบถามอย่างตรงไปตรงมาตามข้อเท็จจริง เพื่อให้ข้อมูลที่สามารถนำไปใช้ได้นั้นมีความเที่ยงตรงและเกิดประโยชน์สูงสุด

ทางผู้วิจัยขอขอบพระคุณทุกท่านที่สละเวลาตอบแบบสอบถาม หากมีข้อสงสัยเกี่ยวกับแบบสำรวจ หรือหัวข้อศึกษาสามารถติดต่อสอบถามเพิ่มเติมได้ที่อีเมล "s.jariyapaktikorn@gmail.com"

คำถามคัดกรองข้อที่ 1

เพื่อคัดกรองข้อมูล

ท่านหรือสมาชิกในครอบครัวมีการประกอบอาชีพเกษตรกรรมหรือไม่ *

- ○ ใช่
- ◉ ไม่ใช่

คำถามคัดกรองข้อที่ 2

เพื่อคัดกรองข้อมูล

ท่านหรือสมาชิกในครอบครัวมีการประกอบอาชีพเกษตรกรรมในพื้นที่จังหวัดพัทลุง สงขลา ตรัง นครศรีธรรมราช หรือไม่ *

- ใช่
- ไม่ใช่

Digital Skills and Technology Possession (6 คำถาม)

ความสามารถในการใช้งานและการถือครองเทคโนโลยี

ปัจจุบันคุณมีโทรศัพท์มือถือสมาร์ทโฟนใช้งานหรือไม่ *

- มี
- ไม่มี

ปัจจุบันคุณมีแท็บแล็ตใช้งานหรือไม่ *

- มี
- ไม่มี

คุณใช้แอปพลิเคชันโซเชียลมีเดียใดบ้าง? (สามารถเลือกได้มากกว่า 1 ข้อ) *

- [ ] Facebook
- [ ] Line
- [ ] X (Twitter)
- [ ] Instagram
- [ ] WhatsApp
- [ ] ไม่ใช้

คุณรู้จักแอปพลิเคชันการเกษตรเช่น แผนที่ทางการเกษตร, ระบบน้ำอัตโนมัติ, เครื่องวัดความชื้นในดิน, อื่นๆหรือไม่? *

- ◯ รู้จัก
- ◯ ไม่รู้จัก

โมเดลการยอมรับเทคโนโลยี (Technology Acceptance Model or TAM) (20 คำถาม)

ความตั้งใจในการยอมรับหรือนำเทคโนโลยีทางการเกษตรมาใช้(2 คำถาม)

คำชี้แจง : โปรดเขียนเครื่องหมายลงในช่องหรือกรอกข้อมูลที่ตรงกับความเป็นจริงของท่านมากที่สุด
ระดับ 1 หมายถึงไม่เห็นด้วยอย่างยิ่ง

ระดับ 2 หมายถึงเห็นด้วยน้อย

ระดับ 3 หมายถึงเห็นด้วยปานกลาง

ระดับ 4 หมายถึงเห็นด้วยมาก

ระดับ 5 หมายถึงเห็นด้วยอย่างยิ่ง

คุณตั้งใจจะใช้เทคโนโลยีการเกษตร (เช่น แผนที่ทางการเกษตร, ระบบน้ำอัตโนมัติ, หรือ เครื่องวัดความชื้นในดิน) ในอนาคตมากน้อยอย่างไร *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

คุณคิดว่าคุณมีโอกาสจะยอมรับนำเทคโนโลยีการเกษตรใหม่ๆ มาใช้งานภายในปีหน้า *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

การรับรู้ถึงประโยชน์ (Perceived Usefulness or PU) (3 คำถาม)

คุณมีความเห็นอย่างไรกับการใช้เทคโนโลยีการเกษตรมาแล้ว จะช่วยเพิ่มผลผลิตทางการเกษตรของคุณ *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

คุณมีความเห็นอย่างไรกับเทคโนโลยีการเกษตร จะสามารถช่วยให้การทำการเกษตรมีประสิทธิภาพมากขึ้น *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

คุณมีความเห็นอย่างไรกับนำข้อมูลจากเทคโนโลยีการเกษตร มาช่วยให้การตัดสินใจของคุณในการทำการเกษตรได้ดียิ่งขึ้น หรือ แม่นยำยิ่งขึ้น *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

การรับรู้ถึงความง่ายในการใช้ (Perceived Ease of Use or PEOU) (3 คำถาม)

คุณมีความเห็นอย่างไรกับ การเรียนรู้การใช้เทคโนโลยีด้านการเกษตรเป็นเรื่องง่ายสำหรับคุณ *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

ฉันพบว่าเทคโนโลยีการเกษตรใช้งานง่าย *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

การใช้เทคโนโลยีการเกษตรต้องใช้ความพยายามที่น้อย *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

ทัศนคติต่อการใช้เทคโนโลยี (3 คำถาม)

ฉันมีทัศนคติเชิงบวกต่อการใช้เทคโนโลยีการเกษตร *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

ฉันเชื่อว่าการใช้เทคโนโลยีการเกษตรมีประโยชน์ต่อสวนของฉัน *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

ฉันพึงพอใจกับเทคโนโลยีการเกษตรที่ฉันได้ใช้ *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

หัวข้อคำถามหลัก (3 คำถาม)

เพื่อนชาวเกษตรกรเห็นว่าฉันควรใช้เทคโนโลยีการเกษตร *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

คนในชุมชนของฉันสนับสนุนการใช้เทคโนโลยีการเกษตร *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

ครอบครัวของฉันคิดว่าฉันควรใช้เทคโนโลยีการเกษตร *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

การแสดงผลลัพธ์ (2 คำถาม)

ฉันสามารถเห็นประโยชน์ของการใช้เทคโนโลยีการเกษตรได้อย่างชัดเจน *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

ผลลัพธ์ของการใช้เทคโนโลยีการเกษตรมีความชัดเจนและเป็นบวก *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	○	○	○	○	○	เห็นด้วยอย่างยิ่ง

คำถามเพิ่มเติมเกี่ยวกับการใช้เทคโนโลยีการเกษตร (5 คำถาม)

คุณใช้เทคโนโลยีการเกษตรใดในปัจจุบัน? (เลือกทั้งหมดที่ใช้) *

- ○ เครื่องมือการทำฟาร์มแบบแม่นยำ
- ○ แอปพลิเคชันมือถือ
- ○ โดรน
- ○ ระบบน้ำอัตโนมัติ
- ○ ไม่ใช้

คุณใช้เทคโนโลยีการเกษตรบ่อยแค่ไหน? *

- ○ ทุกวัน
- ○ ทุกสัปดาห์
- ○ ทุกเดือน
- ○ นานๆครั้ง
- ○ ไม่เคย

คุณเคยได้รับการฝึกอบรมเกี่ยวกับการใช้เทคโนโลยีการเกษตรหรือไม่? *

- ◯ เคย
- ◯ ไม่เคย

คุณยินดีที่จะเข้าร่วมการฝึกอบรมเกี่ยวกับการใช้เทคโนโลยีการเกษตรหรือไม่? *

- ◯ ยินดี
- ◯ ไม่ยินดี

คุณคิดว่าคุณมีความต้องการที่จะนำเทคโนโลยีมาใช้เพื่อการเกษตรมากน้อยอย่างไร? *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	◯	◯	◯	◯	◯	เห็นด้วยอย่างยิ่ง

คุณคิดว่าคุณมีความต้องการที่จะนำเทคโนโลยีมาใช้เพื่อการเกษตรมากน้อยอย่างไร? *

	1	2	3	4	5	
ไม่เห็นด้วยอย่างยิ่ง	◯	◯	◯	◯	◯	เห็นด้วยอย่างยิ่ง

อายุของคุณคือเท่าไหร่? *

- ต่ำกว่า 30 ปี
- 31-40 ปี
- 41-50 ปี
- 51-60 ปี
- มากกว่า 60 ปี

เพศของคุณคืออะไร? *

- ชาย
- หญิง
- LGBTQ+
- ไม่ประสงค์ระบุ

คุณอาศัยอยู่ในจังหวัดใด *

- พัทลุง
- นครศรีธรรมราช
- ตรัง
- สงขลา

ระดับการศึกษาสูงสุดของคุณคืออะไร? *

- ไม่มีการศึกษาอย่างเป็นทางการ
- ประถมศึกษา
- มัธยมศึกษา
- มัธยมศึกษาตอนปลาย
- อาชีวศึกษา
- ปริญญาตรี
- สูงกว่าปริญญาตรี

คุณปลูกพืชประเภทใดเป็นหลัก? *

- ยางพารา
- พืชผลไม้ ยืนต้น ต่างๆ เช่น ทุเรียน มังคุด ลองกอง เป็นต้น
- ทั้งสองอย่าง คือ ยางพารา และพืชผลไม้ ยืนต้น
- พืชอื่นๆ โปรดระบุ

ขนาดที่ดินในการเพาะปลูกของคุณคือเท่าไหร่? *

- น้อยกว่า 1 ไร่
- 1-5 ไร่
- 6-10 ไร่
- มากกว่า 10 ไร่

คุณทำเกษตรมานานกี่ปี? *

- น้อยกว่า 5 ปี
- 5-10 ปี
- 11-20 ปี
- มากกว่า 20 ปี

คุณมีรายจากการทำการเกษตรต่อเดือนเท่าไร่? *

- น้อยกว่า 5,000 บาท
- 5,001 - 10,000 บาท
- 10,0001 - 20,000 บาท
- 20,001 - 30,000 บาท
- มากกว่า 30,000 บาท

คุณมีข้อเสนอแนะหรือความคิดเห็นอย่างไรเกี่ยวกับการนำเทคโนโลยีมาใช้ในการทำการเกษตรกรรมของคุณ

ข้อเสนอแนะ *