Uncertain Supply Chain Management 11 (2023) 533–546

Contents lists available at GrowingScience

Uncertain Supply Chain Management

homepage: www.GrowingScience.com/uscm

Risk management in the adoption of smart farming technologies by rural farmers

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A B S T R A C T

Article history:
Received November 18, 2022
Received in revised format December 20, 2022
Accepted February 18 2023
Available online February 18 2023

Keywords:
Adaptable
Adaptation
Agriculture
Sustainable agriculture
Smart farming
Risk reduction strategy
Technology
Technological capabilities
Rural

Smart farming is a feasible solution to help farmers effectively and sustainably manage the potential threats and risks those traditional farmers face, such as product quality, increased production costs, the environment, climate change, natural catastrophes, pests, and inferior goods. Using a survey research design, this research examined smart farming adoption and risk management models by combining the Technology Acceptance Model (TAM) and the Innovation Diffusion Theory (IDT). The research sampled 400 farmers who are members of community enterprises in the northeastern region of Thailand. Data was collected using a questionnaire and analyzed using a statistical package program in four steps: confirmatory factor analysis, path analysis, structural equation model analysis (SEM), and Sobel's test. The findings revealed that government support variables had the most significant influence by adopting smart farming to risk management. Based on the research results, the government can apply this model to create strategies to encourage farmers to adopt smart farming and increase the production efficiency of agricultural products. The farmer can manage the risks of smart farming, which leads to sustainable smart farming and is useful for further academic acceptance and risk management studies. Furthermore, this study contributes to the existing literature on combining TAM and IDT in model adoption and risk management. The limitations include the small sample size adopted and the limited coverage area for the study, which restricts the generalization of the findings. However, the findings offer a glimpse into the benefits of smart farming.

1. Introduction

Thailand's northeastern region is mainly agricultural, lying on the Korat plateau, the second Thai breadbasket. The provinces in Thailand's northeastern region are Roi Kaen Sarasin Province, Roi Et Province, Khon Kaen Province, Maha Sarakham Province, and Kalasin Province. This area is known for its rich culture in agriculture and animal husbandry. As a result, government agencies have pushed the Northeastern region's ongoing expansion of agricultural products (Wichaiyo et al., 2019). However, removing a significant portion of the forest in the 1950s and 1960s altered this condition. For this reason, this region's ground is dry because it does not store water (Wichaiyo et al., 2019). In Thailand's northeastern region, traditional farming still exposes farmers to many risks, including production risks, higher production costs, the environment, climate change, disasters, pests, and poorer products. Farmers try to mitigate these risks by themselves, for example, by choosing appropriate crops and animals for the local environment and improving farmer skills. However, these risk management strategies are unsustainable solutions that necessitate ongoing and unsustainable adaptation. As a result, smart farming is a viable option for assisting farmers in successfully and sustainably managing their possible hazards (Mutambara, 1998; Ndinojuo, 2020).

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doi: 10.5267/j.uscm.2023.2.011

What will happen next in Thailand's agriculture sector is that the agricultural industry must adapt by utilizing technology to improve management efficiency and manage agriculture risks (Kolk, 2021). Furthermore, Thai farmers are becoming increasingly interested in smart farming methods. As can be seen, smart farming is the top topic in the community enterprise group's conversation. As a result, smart farming is becoming increasingly crucial in Thailand's agriculture (Azam & Shaheen, 2018). Previous technology adoption studies look into the motivations or factors that prompted or prompted farmers' decision-making stage of the adoption process to adopt smart technology. On the other hand, it shows that smart technology is accepted before being used. In this research, we focus on the motivation for adopting smart farming. The technology adoption literature emphasizes the adoption of farming, particularly the influencing factors that drive smart agriculture adoption. Related work has recognized that the complexity of smart technologies, their compatibility, and their relative advantages, as perceived by individuals, affect the degree of innovation adoption (Saengavut & Jirasatthumb, 2021).

Smart agriculture refers to precisely managed agriculture that uses science and information technology as a tool to process quickly and accurately. Smart agriculture increases the cost-effective use of available resources, resulting in an increased quantity and quality of produce, reducing production costs, and being safe for consumers and the environment, leading to international competition (Abd-Elaty et al., 2022). Modern technology can be combined with agricultural work in Thailand because agriculture is the main occupation in Thailand. Modern technology has become increasingly important in everyday life, and it is widely used in all professions. Currently, agricultural sector workers have continued to decline (Saengavut & Jirasatthumb, 2021). Therefore, various technologies have been introduced to help farmers manage the risk instead of using human labor in response to market demands leading to a sustainable and environmentally friendly agriculture in the future (Rajakumar et al., 2018)

Therefore, it is imperative to urgently find ways to encourage farmers in Thailand's northeastern region to adopt smart farming instead of traditional farming. This raises the question of the study, "What variables influence farmers in Thailand's northeast to adopt smart farming and risk management?" Therefore, we are interested in researching smart farming acceptance to increase the adoption of smart farming. Because smart farming will increase agricultural product production efficiency and sustainable agriculture and reduce the risks that farmers face, this research will benefit the agencies involved in promoting the adoption of smart farming for small-scale farmers.

2. Literature Review

The current research is founded on three well-established theories, namely the Technology Acceptance Model (TAM) (Davis, 1989), the Innovation Diffusion Theory (IDT) (Rogers, 1983), and Hofstede's Cultural Framework (Hofstede, 1984), with some modifications, extensions, and integrations. TAM is the foundation of the present research paradigm and has been the central skeleton for many types of research on IT adoption (Agarwal & Prasad, 1999; Chau, 1996a; Chau & Hu, 2002; Davis, 1989; Gefen & Straub, 1997; Gillenson & Sherrell, 2002; Hu et al., 1999; Karahanna et al., 1999; Lee et al., 2001; Mathieson, 1991; Taylor & Todd, 1995). Despite its importance, TAM is a changing theory adapted to meet the situation. For instance, it has been noted in the past that IDT complements TAM effectively in terms of boosting its predictive and explanatory capacity (Agarwal & Karahanna, 2000; Agarwal & Prasad, 1998b; Gillenson & Sherrell, 2002; Karahanna et al., 1999; Lewis et al., 2003; Venkatesh et al., 2003; Wu & Wang, 2005). IDT offers TAM with parameters that have been shown to influence individual adoption behavior significantly. Since TAM is being used to investigate Asian culture, cultural considerations will inexorably influence the research theory.

2.1 Technology Acceptance Model

This study is conceptually supported by the Technological Acceptance Model (TAM) (Davis, 1989; Davis et al., 1989). The model's theoretical basis is Fishbein and Ajzen's (1975) Theory of Reasoned Action (TRA). According to the Theory of Reasoned Action, beliefs impact attitudes, which result in intentions that guide or create conduct. Davis (1989) modified the belief-attitude-intention behavior causal chain to forecast user acceptance of information technology. The TAM seeks to predict and explain the adoption of information technology systems by proposing that perceived utility and perceived ease of use are the critical acceptance factors. Prior research has proved the TAM's applicability to various information technology applications (Chin & Gopal, 1995; Gefen & Straub, 1997; Hu et al., 1999; Igbaria et al., 1996). The Technology Acceptance Model (TAM) is derived from the theory of reasoned action (TRA) (Fishbein & Ajzen, 1980) and believes that beliefs impact an individual's acceptance of technology through two variables: perceived utility and perceived ease of use. According to Davis et al. (1989), TAM is intended to explain computer use behavior. Concerning the original TAM, as shown in Fig. 1, it is hypothesized that a person's adoption of technology is instantly impacted by their goal, which is subsequently influenced by their attitude toward usage. Attitude toward usage is simultaneously influenced by both the PU and PEOU components.

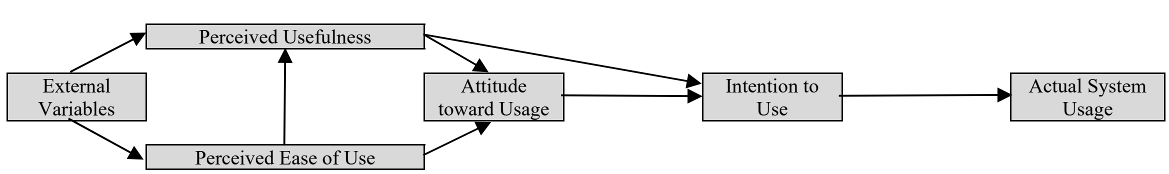

Fig. 1. Original TAM. Source: Davis (1989)

TAM is a widely validated model that demonstrates its theoretical robustness in a variety of contexts, such as online customer behavior (Koufaris, 2002), PC video conferencing applications (Townsend et al., 2001), group support systems (Briggs et al., 2003), telemedicine technology (Chau & Hu, 2002), CASE system (Chau, 1996b), WebCT (Ngai et al., 2007), ERP system (Amoako-Gyampah & Salam, 2004; Igbaria et al., 1995). There are several examples of settings utilized in prior TAM research. Specifically, TAM research is meta-analyzed (Deng et al., 2005) to validate the TAM's fundamental assumptions. In addition, King and He (2006) have determined via their evaluations that TAM's efficacy is supported in numerous systems or domains. TAM is unquestionably one of the most significant ideas for forecasting end-user behavior and technology use. Based on these justifications, TAM is well suited to be the leading theory used in this study by adding new components from another theory and deleting those from the original one. On this basis, a case can be made for using TAM to investigate the adoption of smart framing technology and explore the willingness of farmers to embrace smart farming techniques in place of traditional methods. At the core of smart farming is the application of technology, which posits improved methods and collects data that predicts how to improve past methods for optimum yield.

The Innovation Diffusion Theory (IDT)

Rogers (1983, 1995, 2003) performed one of the first studies on IT innovation uptake at the human level. His 1983 publication is referred to as the Innovation Diffusion Theory (IDT) (Rogers, 1983). According to IDT, individuals should assess the implementation of innovative IT from an information-centric standpoint (Rogers, 1983). According to IDT, individuals tend to build views about the subject innovation based on its qualities while deciding whether to embrace it. The views are shaped by the available and accessible information surrounding the innovation. In this manner, the diffusion of an invention among organizations and people mainly depends on what they learn or communicate about the idea. IDT views innovation diffusion as the result of the preceding process in which an invention is transmitted to the members of a social system via specific channels throughout time (Rogers, 1995).

Given this theory in a smart farming context, IDT-based research focuses on components that contribute to shaping and forming information flow. Among the contributing variables are personal and psychological features, individual propensity to embrace innovation such as social influence, compatibility of the idea with smart farming attributes, etc. The likelihood of smart farming adoption is contingent upon how potential farmers perceive smart farming attributes. Rogers (1995) identifies five innovation characteristics: relative advantage, compatibility, complexity, trialability, and observability. Based on their meta-analysis of the cumulative research findings, Tornatzky and Klein (1982) conclude that relative advantage, complexity, and compatibility consistently contribute to adoption. Other researchers have observed similar results (Agarwal & Prasad, 1998b; Agarwal & Prasad, 1998a; Parthasarathy & Bhattacherjee, 1998; Thong, 1999). The intrinsic features or characteristics of inventions have no impact on IDT. Instead, the adoption rate is influenced by prospective farmers' views of such qualities or smart farming attributes (Moore & Benbasat, 1991; Rogers et al., 2005).

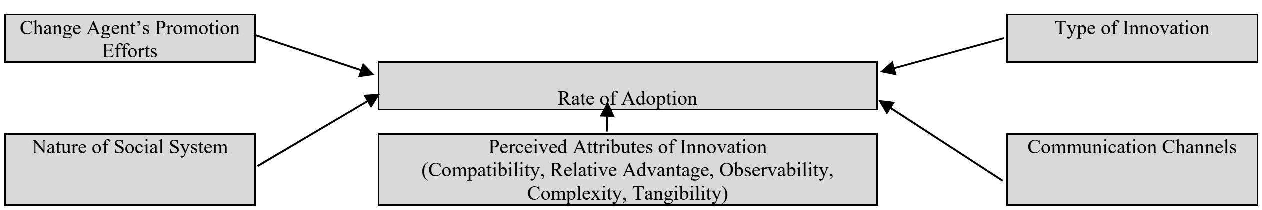

Fig. 2. Innovation Diffusion Theory. Source: Rogers (1983).

Moore and Benbasat (1996) proposed expanding IDT to incorporate two new constructs: social influence and government support. This is incorporated into the current study to evaluate the impact of social influence and government on Thai farmers' adoption of smart farming technology. What social aspects influence farmers to adopt smart farming technology? How does the government support farmers in their efforts to adopt smart farming techniques, given the improved validity and dependability.

Combining TAM with IDT

Although TAM is based on TRA's robust theoretical foundation, it does not fundamentally integrate any of TRA's fundamental assumptions. In TRA, the relationship between behavioral intention and behavior is unconditional, suggesting that whether an action is performed or not is exclusively determined by the behavioral intention. Other than the desire, there are no antecedents for the actual conduct. Nonetheless, the IT environment that TAM mainly addresses has imposed other limits in addition to an individual's desire alone. Dishaw and Strong (1999) stated that social influence and cognitive instrumental processes impact the adoption behavior of technology users (Venkatesh, 2000). The compatibility problem is another factor that TAM does not examine. Compatibility of technology adoption relates to whether the user's existing value system, ideas, and attitudes are compatible with the technology's usage. Research has shown that a higher degree of compatibility correlates with a greater rate of technology adoption (Goodhue, 1995; Goodhue, 1998). Thus, there are always other problems that technology users must address, implying that TAM may have omitted certain variables. In light of the aforementioned and other study findings, the inherent weakness of TAM necessitates incorporating pertinent factors to improve its validity and reliability. These variables may be derived from other models or theories created expressly for the application context of TAM. TAM has been criticized for bypassing essential aspects, which must be combined with another model or theory (Hu et al., 1999; Legris et al., 2003). According to their findings, if this integration is not established, it may be challenging to improve TAM's predictive and explanatory capacity. The TAM constructs of perceived utility and perceived ease of use complement the IDT constructs of relative advantage and complexity, respectively. Some academics say TAM constructs are simply a subset of IDT constructs, while others suggest that combining TAM with IDT might provide a more robust model. For instance, Gillenson and Sherrell (2002) combined IDT with TAM through the compatibility construct to investigate the customer behavior of an online B2C business.

Consequently, TAM and IDT complement one another, and their combination might result in a more rigorous model than either alone. IDT explores the development of a positive or negative attitude toward an invention. Unfortunately, it does not elaborate on how the attitude becomes a choice to accept or reject. TAM (Davis, 1985) provides theoretical connections between beliefs, attitudes, intentions, and actions. Thus, combining TAM with IDT may boost the robustness of both models. The prior studies incorporate TAM and IDT to varying degrees.
IDT, like TAM, is a well-known theory that describes how a social group adopts an invention. IDT is a model at the level of human interactions, verified in several disciplines, including information systems (Lippert & Michael Swiercz, 2005). The current study aims to develop an expanded TAM by including many salient components, verifying the model with consumers, and analyzing technology in Asian culture. Consequently, TAM and IDT are combined to form an important aspect of the current study's research framework.

Social influence: A study by Montes de Oca Munguia et al. (2021) on agricultural innovation adoption models found that social influence factors affect the acceptance of smart farming among farmers. Because farmers feel that people around them are more important to those who accept smart farming than those who do not, it is easier for them to adopt smart farming when social influences are involved. Similarly, Filippini et al. (2020) research on social networks driving technology adoption in Italy focused on studying social influence factors on the acceptance of smart farming. The results showed that social influence factors significantly impacted the adoption of smart agriculture; Nuray and Theuvsen (2020) found a similar effect. The study investigated factors affecting smart farming adoption behavior in Turkey. The results showed that social influence factors significantly influenced the adoption of smart farming behavior. This result is consistent with Klerkx et al.'s (2019) study of digital agriculture, or smart farming. The opinions of people in society or referring to people who were close to users positively influenced the adoption behavior of smart farming. Similar to Ronaghi and Forouharfar (2020), the findings pointed out the importance of social influence on behavioral intention and actual IoT technology adoption. Because farmers are readily driven to adhere to the social norms around the adoption of smart agriculture when it becomes accepted as conventional or standard conduct. Similarly, injunctive norms influence adaptors' opinions on smart agriculture by letting them know the societal consensus. It affects users' future intentions of using the technology or their actual usage patterns once adopted (Joa & Magsamen-Conrad, 2021). Based on the coherence of the above studies, it can be inferred that social influence is positively correlated with the adoption of smart agriculture, hence our research hypothesis 1:

H_1: *Social influence is positively correlated with smart agriculture adoption.*

A government-supported study by Azam and Shaheen (2018) looked at factors affecting farmers' decision-making in smart farming in India. The study found that marketing and government policy factors were the most important in convincing farmers to adopt more smart farming regardless of their level of education. This study shows that it seems unlikely that smart agriculture adoption will be achieved without government support. This result is consistent with a survey by Aryal et al. (2018), who examined the components affecting the adoption of smart farming in Bihar, India. The study results confirm that the government support factor in the issue of access to public education training is a crucial factor contributing to greater acceptance. Similarly, a study by Khandker and Thakurata (2018) that examined factors affecting the adoption of hybrid rice cultivation technology among Indian farmers found that the factors that influenced farmers to turn to mixed rice the most were the availability of government subsidies and seeds and a trend of continuing to grow mixed rice when supported by the government. Amondo and Simtowe (2018) also found that farmers who rejected smart sorghum cultivation technology in Tanzania alternately accepted the technology by accepting and using it for a while, then stopping and never using it again. This was mainly due to the government's lack of serious and consistent promotion. Because the government hired officials to provide knowledge and understanding, funding was injected into the program to encourage farmers to turn to smart sorghum cultivation. This was no longer present as a critical factor in deciding whether to accept or not accept smart sorghum technology in Tanzania. Based on the coherence of the above studies, it can be inferred that government support is positively correlated with the adoption of smart agriculture, hence the second research hypothesis:

H_2: *Government support is positively correlated with smart agriculture adoption.*

Relative benefits of smart farming: a study by Mango et al. (2018) that examined the incentives for farmers to adopt innovative smart bean production in the Antonia region of Mozambique showed that when farmers obtain the relative benefits from smart bean production innovations, the adoption of smart bean production innovations increases. Similarly, Pivoto et al. (2019) examined the factors influencing the adoption of smart farming among Brazilian farmers. It was found that farmers were interested in the benefits of the new farming model and that correlational benefiting factors influenced the farmers' decisions on the new farming practices of southern Brazil. Aamer et al. (2021) examined the adoption of sustainable smart farming using the Internet of Things (IoT), showing that smart farming significantly impacts farmers' choice of smart farming. This result is consistent with a study by Balafoutis et al. (2020) looking at trends in smart farming technology adoption and the adoption of smart farming. Farmers were found to focus on new technology systems that contribute to the efficiency of their operations. Moreover, consistent with Koutsos and Menexes's (2019) research looking at the benefits of adopting smart farming, farmers focused on reducing production costs and increasing profitability. The farmers believed that smart farming would help them gain more production profits, a benefit of smart farming. Therefore, the hypothesis of the third research study is the relative positive correlation between smart farming and the adoption of smart farming:

H_3: *The relative benefits of smart farming have been positively correlated with the adoption of smart agriculture.*

The compatibility of smart agriculture with their farms has been positively correlated with smart agriculture adoption, according to a research study by Takagi et al. (2021) that examined factors affecting the adoption of smart farming by farmers in Taiwan. Farmers found that they attached importance to accepting smart farming based on their perceptions of the new technology. Moreover, farmers were more likely to adopt new technologies if they found that they were compatible with their farms. This is consistent with research by Molina-Maturano et al. (2021) on the adoption of smart farming in Mexico. An interesting factor in the decision to adopt smart farming in this country was the assessment of its compatibility with existing basic living conditions without the farmers having to change their livelihoods too much in accepting smart farming. The result is similar to Kernecker et al. (2020), which found that farmers' prior experience influenced their decision to accept smart farming. This is also consistent with the research done by Prayukvong (2003), who considered the factors affecting farmers' acceptance of alternative agricultural systems in a case study in Khon Kaen Province, Thailand. This was conducted by analyzing the factors affecting the adoption of alternative farming practices, namely farmers' experiences, and traditional thinking. Personal experience is built on the societal backdrop, individual value formation attitudes, and decision-making assessment processes. Saengavut and Jirasatthumb (2021) have shown that farming experience positively impacts professional attitudes toward organic farming and the anticipation that organic agriculture acceptance will spread throughout the farming community. Smart agriculture showed a statistically significant correlation between physical availability and the farmers' livelihoods. Based on the coherence of the above studies, it can be inferred that the compatibility of smart agriculture with the farmers' livelihoods is positively correlated with the adoption of smart agriculture, hence the fourth research hypothesis:

H_4: *The compatibility of smart agriculture with the farmers' livelihoods is positively correlated with their farms*

Optimism: Parasuraman and Colby (2015) found that technology allows more flexibility and makes everyday tasks more efficient. Several researchers have examined how optimism about technology affects the intention to use it (Pfeiffer et al., 2021; Sharifuddin et al., 2018; Clark et al., 2019). Pfeiffer et al. (2021) found that general attitudes about farming knowledge and trust in farmers are positive. This includes the optimism of the farmers themselves, which makes it easier to accept smart farming. Moreover, in line with Sharifuddin et al. (2018) and Clark et al. (2019), positive farmer attitudes influence the acceptance of smart farming in Indonesia. In addition, Nyang'au et al. (2021) found that climate-smart agriculture practices were linked to household size, monthly income, loan availability, and farmers' perceptions of climate change. Based on the coherence of the above studies, it can be inferred that optimism about smart farming is positively correlated with the adoption of smart farming. Hence the fifth research hypothesis:

H_5: *Optimism about smart farming is positively correlated with smart agriculture adoption.*

Interest in smart farming: Nyasimi et al. (2017) reviewed the interest in smart farming and the social influence necessary for the continued development of smart farming. Smart farming or not: those with a higher interest in smart farming than the adoption of smart farming would positively impact others. Michels et al. (2021) examined farmers' acceptance of drones in farming. Farmers who were determined to use drones on their farmland were more likely to adopt drones later, in line with the work by Montes de Oca Munguia et al. (2021), which examined several factors affecting the use of drones. It influences the acceptance of agricultural innovation by analyzing various complex data factors that affect such acceptance, and require the self-acceptance of farm innovations by those who want to initiate new farming practices. Based on the arguments and viewpoints inferred from the cited literature, it can be deduced that interest in smart farming is positively correlated with the adoption of smart agriculture, hence the sixth research hypothesis:

H_6: *Interest in smart farming is positively correlated with smart agriculture adoption.*

Risk management: Several studies on risk management, including Asfaw et al. (2018), considered farmers who accepted smart weather warning systems using satellite data. This allows farmers to mitigate climate risks to crop yields at the beginning of the season, enabling them to assess the feasibility and manage resources to mitigate potential risks of climate change. A study by Gurkan et al. (2020) found that the adoption of applications and software systems among farmers helped provide accurate early warning of upcoming weather conditions and alert the farmer to potential hazards, giving them time to prepare or solve problems that can be mitigated. Potential risks that can result in farmers making more profits are also found in Schimmelpfennig (2016), which studies farm profits and smart farming adoption by corn and soy farmers in the United States.

It was found that farmers who embraced smart farming could help predict the variability of their crops, thereby reducing their risks and enabling them to plan their response to potential threats. Likewise, Aryal et al. (2018) found that decisions to adopt smart farming gave farmers more access to climate information. Farmers can manage the risks that may affect their farming, enabling them to consider reducing the loss of their crops through smart farming. Based on the coherence of the above studies, it can be inferred that the adoption of smart farming is positively correlated with risk management.

H_7: *The adoption of smart agriculture is positively correlated with risk management*

3. Methods

This research adheres to international research ethics and complies with the Declaration of Helsinki, which was approved by the Human Research Ethics Assessment Document No. HE-65-3092 on April 11th, 2022, by the Khon Kaen University Human Research Ethics Committee. The research team in this study used quantitative research techniques by making use of the research techniques outlined below.

The population of this research was farmers who were members of a community enterprise group engaged in organic farming in Roi Et Province, Khon Kaen Province, Maha Sarakham Province, and Kalasin Province in the northeastern region of Thailand. This area was selected because the community enterprise has begun to accept smart agriculture. The provinces of Roi Et Province, Khon Kaen Province, Maha Sarakham Province, and Kalasin Province, provinces in the North-Central Province Group of Thailand, were purposively selected for this study. According to the 4-year regional development strategic plan (2015–2018), strategy one is to promote safety and quality in the production and export of agricultural products and standardized industrial agriculture, and strategy two is to strengthen the sustainable agriculture sector.

Sampling method: the study employed a judgmental sampling method. The nature of the sample must be considered under the research objectives. The research team used the sample group because the sample must accept smart farming. There were several screening questions before completing the questionnaire. Is your farm currently using smart farming technologies? If the respondents answered "No" to the screening question, they were excluded from the sample. However, if the respondents answered the screening question "Yes," they were considered a well-qualified sample for further study.

The sample size: This study quantitatively determined the population size, i.e., the number of community enterprise groups in Roi Et Province: 4,106; Khon Kaen Province 2,638, Maha Sarakham Province 2,619; and Kalasin Province 1,813. The first step was quota sampling by calculating a portion of the number of groups of agricultural community enterprises in each province, divided into Roi Et Province 147, Khon Kaen Province 94, Maha Sarakham Province 94, and Kalasin Province 65, for a total of 400 community enterprise groups. The authors used a computational method based on Allen et al. (1977) to calculate the sample size. The 95 percent confidence level and the 5% error level were determined. For ease of evaluation, a sample size of at least 384 people was required to estimate the percentage with no more than a 5 percent error at a 95 percent confidence level. The researcher used 400 samples that met the criteria specified by the conditions. The second step was judgment sampling, in which the authors determined the samples from agricultural community enterprises, who are the key people, representatives, chairmen, or heads of each community enterprise.

The research tool was a questionnaire that the respondents could answer by self-administration. The screening question was: "Are you a farmer who has used smart farming technology within the last year?" If the respondents answered yes, then they were a research sampling target. However, if the respondents answered no, they were not real targets. The questionnaire consisted of nine parts: Part One is the general information about the respondents, compiled by the researcher. It consisted of five questions. Part two, social influence, is adapted from the studies of Venkatesh et al. (2003), Asfaw et al. (2018), and Mango et al. (2018). It consisted of five questions. Part three, government support, is adapted from the study of Sutthichaimethee et al. (2019). It consisted of five questions. Part four, relative benefits of smart farming, adapted from the study of Caffaro and Cavallo (2019), consisted of five questions. Part five is on the compatibility of smart agriculture with farmers' livelihoods, as revised by Godoe and Johansen (2012). It consisted of five questions. Part six, optimism on smart farming, adapted from the study of Parasuraman (2000) and Walczuch et al. (2007), consists of five questions. Part seven, interest in smart farming, adapts from the studies of Parasuraman (2000), Walczuch et al. (2007), and Godoe and Johansen (2012). It consisted of five questions. Part eight, the adoption of smart farming, was revised by Watson et al. (2016). It consisted of five questions. Part nine, risk management, adapts from the study of Watson et al. (2016). It consisted of eight questions. A Likert scale feature with five levels to choose from was used.

Validity: Confirmatory Factor Analysis (CFA) was used to test the model's validity, with the component value of the factor relationship ranging between 0.755 and 0.952. The reliability is accurate because the value is higher than 0.75 (Hair Jr et al., 2010), and checking the quality of content validity (Content Validity) by bringing the questionnaire for consultation by three experts.

Reliability: The revised questionnaire was tested (pilot test) with 30 samples from the community enterprises that were not used in the main research. In this preliminary investigation, the community enterprises in Nakhon Ratchasima Province were pilot-tested because they were the most similar to the target group, including weather conditions and soil characteristics. The questionnaires returned from all trials were then used to determine the confidence value using Cronbach's Alpha Coefficient method (Cronbach, 1970). The confidence test with Cronbach's Alpha Coefficient was between 0.762 - 0.877, indicating that the questionnaire was reliable because the result was higher than the threshold of 0.7 (Hair Jr et al., 2010).

Data analysis: The information gathered from the questionnaire was used to check the completeness of the information obtained. Performance data processing was done with a prepared computer program from SPSS for the statistical values. The three steps used in data analysis were as follows: 1. Path analysis analyzes the influence or cause of the progenitor variable on the dependent variable. 2. Structural equation modeling technique used for hypotheses analyses between several primary variables and simultaneously passing the mediator to the dependent variable. 3. Analysis of interstitial variables (Sobel's test) to test the intermediate variables for the acceptance of smart agriculture as being able to act as a good mediator between social influences, government support, relative benefits of smart farming, optimism about smart farming, interest in smart farming and how the compatibility of smart agriculture and the farmers' livelihoods passes to risk management.

4. Results

The questionnaire was sent to 400 of the community enterprise's leaders. The distribution of the sample is summarized on Table 1:

Table 1
Demographic information of respondents

	Frequency	Percent (%)
Genders		
Male	163	40.8
Female	237	59.3
Ages		
18 and below	116	29.0
19-30	120	30.0
31-40	107	26.8
41-50	28	7.0
51-60	29	7.2
61 and over	116	29.0
Educational levels		
Primary school	13	3.3
Junior High school	131	32.8
High school	117	29.3
Bachelor’s degree	139	34.8

Analysis of the relationships between variables (multicollinearity), when considering the correlation coefficient between the eight observed variables, found that the correlation coefficient between all variables was positive, indicating the relationship was in the same direction with values between 0.190 and 0.846 with a statistically significant level of $P<0.05$, as shown in Table 2, indicating that all variables are consistent with the conceptual and theoretical framework of the researcher-created structural equation model (Tabachnick et al., 2007).

Table 2
The correlation coefficient matrix between the observed variables.

	SOC	GOV	BEN	VAL	OPT	INT	ADO	RIS
SOC	1							
GOV	.708**	1						
BEN	.669**	.578**	1					
VAL	.570**	.490**	.665**	1				
OPT	.472**	.406**	.673**	.553**	1			
INT	.515**	.432**	.506**	.423**	.568**	1		
ADO	.457**	.409**	.470**	.378**	.561**	.638**	1	
RIS	.333**	.303**	.299**	.353**	.320**	.413**	.333**	1

Note *$p < 0.05$ was statistically significant at the .05 level.

From Table 2, when considering the relationship between each variable, government support and social influence, the correlation coefficient was highest at 0.708, followed by the relative benefit of smart farming and social impacts, with a correlation coefficient of 0.669. In contrast, risk management and the relative advantage of smart farming had the lowest correlation coefficient of 0.299.

Path Analysis for hypothesis testing

The researcher analyzed the relationship between the variables in the model using path analysis, one of the concepts used in structural equation modeling analysis. It found the relationship between variables by using the maximum likelihood estimation method. Using a packaged program based on the statistical significance level of 0.05 ($P<0.05$), the results of the analysis gave path coefficients as follows:

Table 3

The causal relationship influence between variables and hypothesis testing

Hypothesis	Influence	Hypothesis Testing Total	Results
H1: Social influence is positively correlated with smart agriculture adoption.	DE = .012 IE = .050	TE = .062	Accept
H2: Government support is positively correlated with smart agriculture adoption.	DE = .037 IE = .190	TE = .227	Accept
H3: The relative benefits of smart farming have been positively correlated with smart agriculture adoption.	DE = .020 IE = .180	TE = .200	Accept
H4: The compatibility of smart agriculture with the farmers' livelihoods is positively correlated with smart agriculture adoption.	DE = .102 IE = .250	TE = .270	Accept
H5: Optimism about smart farming is positively correlated with smart agriculture adoption.	DE = .020 IE = .110	TE = .130	Accept
H6: Interest in smart farming is positively correlated with smart agriculture adoption.	DE = .170 IE = .196	TE = .336	Accept
H7: The adoption of smart agriculture is positively correlated with risk management.	DE = .671	TE = .671	Accept

Note *p < .05 was statistically significant at the .05 level.

From Table 3, government support, relative benefits of smart farming, compatibility of smart agriculture with the farmers' experience, and interest in smart farming have a causal relationship with the acceptance of smart farming and risk management. The test results thus confirm all established assumptions.

Structural equation modeling

Considering the relationship between the models and empirical data, the statistical value $\chi 2/df$ should be less than 3.00. The probability of testing the variance matrix of variables in the estimated model with the empirical data must exceed the statistical significance level of 0.05 ($p > 0.05$). This means that the model is consistent with the data. The harmonization index must be greater than 0.90, i.e., the goodness of fit index (GFI), the comparative fit index (CFI), and the non-conformance index or residual index must be less than 0.08: RMSEA (root mean square error of approximation) and root mean square error of standard error (standardized root mean squared residual: SRMR) were calculated. The results indicate that the intervariable relationship model is consistent with the empirical data, with the statistical values meeting all specified criteria.

Table 4

Results for determining the concordance of the direct influence path analysis model

Statistic	Criteria for Consideration	Value	Evaluation Results
χ^2	-	2.145	-
df	-	2	-
χ^2/df	It should be less than 3.00	1.072	Pass
p	It should be greater than 0.05	.056	Pass
CFI	It should be greater than 0.90	.965	Pass
GFI	It should be greater than 0.90	.923	Pass
RMSEA	It should be less than 0.08	.049	Pass
SRMR	It should be less than 0.08	.046	Pass

Note *p was statistically significant at the 0.05 level.

Mediator variable influence test (Sobel's test)

The mediator variable testing uses Sobel's test to explain what variables influence the adoption of smart farming. The adoption variable for smart farming is the mediator variable in the transmission of influence between variables. The influence characteristics of interstitial variables can be demonstrated through Sobel's test as is presented in Table 5:

Table 5

Characteristics of the indirect influence of independent variables on dependent variables through central variables

Hypothesis	β	Sobel's test(z)	The effect of the mediator variable
H1: Social influence is positively correlated with smart agriculture adoption.	0.504	0.667	Partial
H2: Government support is positively correlated with smart agriculture adoption.	0.357	0.721	Partial
H3: The relative benefits of smart farming have been positively correlated with smart agriculture adoption.	0.996	0.423	Partial
H4: The compatibility of smart agriculture with the farmers' livelihoods is positively correlated with smart agriculture adoption.	0.552	0.593	Partial
H5: Optimism about smart farming is positively correlated with smart agriculture adoption.	0.392	0.684	Partial
H6: Interest in smart farming is positively correlated with smart agriculture adoption.	0.012	0.314	Partial

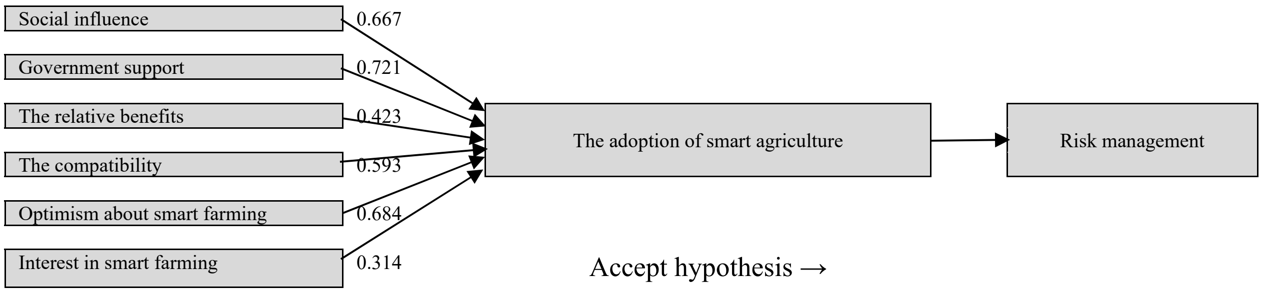

Fig. 3. The correlation of the independent variables on dependent variables through mediator variables

5. Discussion

The findings from the study about risk management in the adoption of smart farming technologies by rural farmers revealed that social influence was positively correlated with the adoption of smart agriculture and was the third influencing factor at a statistically significant 0.05. It can predict the emergence of smart farming adoption and risk management by 66%. If a farmer is influenced by someone they trust, such as a family member, friend, or farmer group leader, they are more likely to accept smart farming. As farmers focus on the advice from a person they can talk to and learn about smart farming, they will decide on the acceptance of smart farming by listening to others. These people considerably influence a farmer's decision to accept smart farming. The present research shows that social influence is positively correlated with the adoption of smart agriculture. The results are consistent with previous research by Filippini et al. (2020), who studied social networks driving technology adoption in Italy.

Moreover, Eweoya et al. (2021) inferred that the extent to which others perceive an individual's capacity or expectation to use a system is social influence. As a result, social influence directly impacts users' adoption of smart agriculture (farmers). The results showed that social influence factors had a significant direct impact on the adoption of smart farming. Nuray and Theuvsen (2020) found a similar effect when investigating factors affecting Turkey's smart farming adoption behavior. The research applied the principles of UTAUT theory as a basic conceptual framework for explaining the farmer's acceptable behavior for smart farming. The results showed that social influence factors significantly influenced the adoption of smart farming. The result is consistent with Klerkx et al.'s (2019) study of digital agriculture, or smart farming. It was found that the opinions of people in society or referring to people close to the users positively influenced farmers to adopt smart farming behavior.

Government support was positively correlated with the adoption of smart agriculture at a statistically significant 0.05 and had the most substantial influence. It was able to predict the emergence of smart farming adoption and risk management by up to 72%, explaining that farmers will have a higher degree of acceptance of smart farming if they receive sufficient government support because farmers in Thailand pay more attention to government support. Farmers want the government to thoroughly and continuously promote smart farming. Farmers imagine that smart farming is still distant and improbable, requiring farmers to get government support to increase their level of acceptance of smart farming. This is consistent with a study by Aryal et al. (2018) that examined the components affecting the adoption of smart farming in Bihar, India. The study results confirmed that the government support factor in the issue of access to public education training was a key factor contributing to greater acceptance. Similarly, a study by Khandker and Thakurata (2018), who examined factors affecting the adoption of hybrid rice cultivation technology among Indian farmers, found that the most critical factors that influenced farmers to turn to mixed rice were the availability of government subsidies and seeds and a trend of continuing to grow hybrid rice when supported by the government.

The relative benefit of smart farming was positively correlated in the fifth place with the adoption of smart farming at a statistically significant value of 0.05. It predicted the emergence of smart farming adoption and risk management by 42%. If smart farming had sufficient relative benefits for farmers, this would increase smart farming adoption as Thailand farmers focus on and expect relative benefits from adopting smart farming, such as cost-effectiveness, convenience, and sustainability. If farmers get enough benefits from smart farming, they will be more accepting of it. This result is in line with previous research by Pivoto et al. (2019), who examined the factors influencing the adoption of smart farming among Brazilian farmers. It was found that farmers were interested in the benefits of the new farming model. The relative benefit factors influenced farmers' decisions about the latest farming practices by southern Brazilian farmers. Furthermore, similar to Aamer et al.'s (2021) study about adopting sustainable smart farming using the Internet of Things (IoT). The result found that the benefits farmers will gain from smart farming significantly impact farmers' choice of smart farming. Amade et al. (2020) found innovations that relative benefits of smart farming create farm effectiveness by improving productivity, efficiency, and cost-saving, have a good impact on adoption, and will positively influence its adoption.

The compatibility of smart agriculture with the original values of farmers was positively correlated with the adoption of smart agriculture as the fourth factor at a significance of 0.05. It predicted the emergence of smart farming adoption and risk management by 59%, explaining that if the farmers' livelihoods were sufficiently conducive to smart farming, the level of adoption of smart farming would significantly increase because farmers in Thailand have traditional farming practices that have been passed down through generations as part of their lifestyle. As a result, farmers are attached to livelihoods cultivated for a long time. Smart farming is a new thing that has just come in, forcing farmers to adapt and change the old attitudes from traditional farming to smart farming. However, the change must be gradual and not affect or completely erase the ancient livelihoods of agriculture. As a result, farmers will have an increased acceptance of smart agriculture. The result is in line with a previous study by Takagi et al. (2021) that found that the compatibility of smart agriculture with the farmers' livelihoods affects the adoption of smart farming. Similarly, Molina-Maturano et al. (2021) indicate that one exciting factor in accepting smart farming is age and discretion, assessing compatibility with existing basic living conditions without the farmers changing their livelihoods too much.

Optimism about smart farming was positively correlated with adopting smart farming at a statistically significant level of 0.05 and was the second most influential factor. It predicted the emergence of smart farming adoption and risk management by 68%. If the farmer is a person who thinks positively, then they will be ready to accept new things and be prepared to learn new techniques. They will be up to date with modern technology, resulting in farmers taking smart agriculture more readily because most of the farmers in Thailand are middle-aged and old-age farmers and still adhere to traditional farming. Moreover, they still make farming based chiefly on their feelings or experience. As a result, farmers in this group are still not open to learning new things. Therefore, a positive attitude and optimism about smart farming lead to farmers opening up to new methods, and farmers will have an increased acceptance of smart agriculture. The result shows that if farmers are optimistic enough to have a positive attitude, they will have an increased acceptance of smart agriculture. Optimism was positively correlated with the adoption of smart farming, consistent with a previous study by Pfeiffer et al. (2021), who found that general attitudes about farming, knowledge, and trust in farmers are related to positive thinking. In addition, such optimism results in an easier adoption of smart farming. It is also consistent with Sharifuddin et al. (2018) and (Clark et al., 2019), who found that positive farmer attitudes affect smart farming adoption in Indonesia.

Interest in smart farming was positively correlated with adopting smart farming at a statistically significant level of 0.05 and was the sixth influential factor. It can predict the emergence of smart farming and risk management adoption by up to 31%. If farmers are already interested in smart farming, they need stimulation, and it will be easier for them to accept smart farming. Knowledge and awareness of the benefits that farmers can get from smart farming will stimulate farmers to be interested in trying smart farming. If they are interested enough in smart farming, they can easily accept smart farming. This result corresponds to previous research by Molina-Maturano et al. (2021) studying the adoption of smart farming in Mexico. They found that smart and optimistic farmers are more likely to accept smart farming than others. This result is similar to Kernecker et al. (2020), who found that positive thinking influenced farmers' decision to accept smart farming.

The adoption of smart agriculture was significantly positively correlated with risk management at 0.05. It could predict the occurrence of smart farming adoption and risk management by 67%. The result indicates that a farmer who adopts smart farming will be able to manage the risks associated with their farms, such as resource allocation in production, risks in farm management, and decisions, including the risks from weather conditions. As most of Thailand's agriculture favors seasonal crops, predicting the weather via personal experience is expected, which leads to an inevitable risk that farmers will face. However, when farmers accept smart farming, they will control their farms' costs and resources and reduce unnecessary wastage. The result shows that farmers can manage such risks using smart farming. Risk management and outcomes are consistent with a previous study by Asfaw et al. (2018), examining farmers who accepted smart farming with weather-related early warning systems using satellite data and ground-based measurements. An agricultural early warning system (TAMSAT-ALERT) can help farmers mitigate climate risks to their farming yields. At the beginning of the season, farmers can assess the feasibility and manage resources to reduce the potential risks of climate change. Consistent with a study by Gurkan et al. (2020), it was found that the adoption of applications and software systems among farmers helps to provide accurate early warning of upcoming weather conditions and alerts the farmer to the possibility of potential hazards, giving farmers more time to prepare for or solve problems that can be mitigated. Recognizing potential risks has resulted in more profits for farmers. The main implication of this research is that a model of smart farming adoption and risk management is utilized for farmers and farming in Thailand, which also positively impacts their future operations and the sustainability of the farming enterprise. Practical implications are developed to encourage traditional farmers' adoption of smart farming.

6. Conclusion

Consumer demand is rising due to the increasing global population; smart farming has been identified as one of the methods of developing the Thai agriculture sector to meet the rising demand. Smart farming adoption depends on farmers' acceptance of government support and optimism about smart farming. Identifying critical factors influencing farmers' intentions to adopt smart farming and risk management is essential to predict farmers' behaviors better. Based on theoretical research, we built a model that can be used to study smart farming adoption and risk management.

According to the finding, farmers should be supported and encouraged to access and learn how to utilize smart farming by the government to raise awareness and improve their experience with smart farming. Based on these results, it is highly recommended that the government and government agencies, as well as agricultural stakeholders, provide opportunities for the use of smart farming so that farmers may utilize it to promote and increase agricultural efficiency. One appropriate approach is for the Department of Agriculture to support the use of smart technology in the agriculture sector, specifically in partnership with the business sector. Farmers may quickly and conveniently get the information they need for their agribusiness via this collaboration. Farmers will also be more receptive to using smart agricultural technology in the future as they become more knowledgeable about it.

Second, we propose that those involved in Thailand's agricultural industry help local farmers become more adept at using smart farming by honing their confidence-building skills. Smart agricultural approaches and procedures will improve management capabilities, awareness, and information. The concept aims to use smart technology to increase output and resilience by providing farmers with information, experience, and agricultural skills throughout their careers. Then, enhance the knowledge and skills of agricultural promoters so that they may impart them to farmers, especially young, innovative farmers, who have the potential to gain from new production-enhancing technologies. The administration of Thai agricultural goods in the digital era involves working with critical authorities from all sectors, setting up farm management tasks, and promoting future agricultural models. Additionally, support and promote smart farming by providing farmers with knowledge and technology at a reasonable cost and by using digital technology and information to organize changes to the production process. Increase agricultural output in terms of value and quantity per area, as well as production productivity, and replace conventional production in line with market needs.

The main contributions of this study are as follows. This empirical research uses structural equation modeling (SEM) to identify smart farming adoption and risk management-related characteristics, enhancing the literature on smart farming.

There are a few limitations to this study. First, this study is susceptible to the inherent limits of measurement errors, as with any study using a survey-based methodology. However, because this research mainly focuses on Thai farmers, it is possible that the results may not apply to the smart agricultural sector in other nations. Farmers from various countries will therefore be the subject of future research to verify the applicability of the theoretical model presented in this study. It is also suggested that future studies test qualitative survey techniques to ascertain if new emerging acceptability conditions will be uncovered based on the different approaches from a quantitative survey.

Acknowledgment

This paper is a part of a research project entitled "Factors Affecting Smart Farming Adoption and Risk Management: A Case Study of Community Enterprises in Roi Kaen Sarasin." Funding was provided by the Faculty of Business Administration and Accountancy of Khon Kaen University during the Fiscal Year of 2020 and under the project of SUstainable developmeNt Smart Agriculture Capacity (SUNSpACe), co-funded by the Erasmus+ Program of the European Union, reference 598748-EPP-1-2018-1-FREPPKA2-CBHE-JP (2018-3228/001-001).

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