Influence of Demographic Characteristics and Extrinsic Motivations on Farmers' Smart Farming Adoption in Northeastern Thailand

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ABSTRACT

This research study aimed at examining the extrinsic motivations that can influence farmers' adoption of Smart Farming and the differences in the demographic characteristics that result in variations in the adoption of Smart Farming in Northeastern Thailand. For this investigation, quantitative research, using the field survey method, was employed. The sampling method was convenient sampling, and the data was collected from 400 farmers in the Northeastern region of Thailand. The data were analyzed using the Structural Equation Model Analysis (SEM) to test the research hypotheses. The study results showed that the differences in demographic characteristics, gender, age, education, and income, had resulted in different adoptions of Smart Farming. Furthermore, the research results showed that the extrinsic motivations (i.e., social motivation, governmental support, and the relative benefits gained from Smart Farming) had, with a statistical significance, influenced the adoption of Smart Farming techniques by farmers in Northeastern Thailand. The highest influential motivation had been governmental support, followed by the relative benefits gained from smart farming and social motivation. The research results can create strategies from external motivations to increase the farmers' acceptance of Smart Farming.

1. INTRODUCTION

An adoption by any individual occurs as a process of receiving the first impression, being persuaded, and making a decision. Once a decision has been made, the action occurs. Based on the individual's critical factors and the nature of the adoption, this process can be either slow or fast. Therefore, if an individual receives one of these and deems it to be better with pleasure, then acceptance will occur. The individual's behavior can be clearly expressed to other people. This is the real adoption [1], especially concerning the adoption of new technology. In other words, the decision to adopt technology is a better and more useful approach [2].

Although Smart Farming is prevalent in many countries worldwide, especially in Northeastern Thailand, farmers continue to utilize the traditional farming methods because these methods are tied to the farmers' livelihoods [3]. Almost all Thai agriculture uses local animals instead of agricultural technology, resulting in low-quality and low-margin yields [4]. Therefore, a shift from traditional farming to Smart Farming is needed. Smart farms are concerned with technology, and farmers consider what is right for the farm's situation. Then they do what is best, what is in alignment with their farm's abilities, and what is consistent with the philosophy of Sufficiency Economy [4]. The Thai government believes that Smart Farming 4.0 will enhance the well-being of all farmers.

Presently, the adoption of modern technology is increasingly playing a greater role in daily life. It is widely used in all fields, especially in farming, a crucial career in Thailand. Hence, when combined with farming, the introduction of modern technology is considered to be Smart Farming. It consists of a new type of farming method, which uses various technologies with high accuracy to assist in completing the work by prioritizing the consumer's safety, the environment, and the most cost-effective use of resources [5]. In the era of declining labor, the agricultural sector needs to apply technology to increase production efficiency.

Moreover, it can help farmers by increasing their operational efficiency, reducing the number of laborers, decreasing working hours, minimizing possible risks, and saving farming costs [6]. In addition, there is an expanding number of online social networks that are awakening the agricultural sector. Thus, farmers are increasingly interested in Smart Farming. Moreover, they are starting to form community enterprises, which are causing adaptations within the agricultural sector. Consequently, Smart

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Farming is becoming increasingly important in the agricultural industry in Thailand [7].

This research study focused on the extrinsic motivations that have influenced the farmers' adoption of Smart Farming and the differences in demographic characteristics that have resulted in different types of adoption of Smart Farming in Northeastern Thailand in order to obtain agricultural benefits and to allocate resources efficiently. Moreover, its adoption can lead to more sustainable and environmentally friendly farming as well.

2. LITERATURE REVIEW

Demographic characteristics: This refers to personal information, such as gender, age, educational level, and income. These influence behavioral expressions and other relevant factors. The different demographic characteristics result in different behavioral expressions, thoughts, and attitudes related to other factors [8]. More recently, research by [9] studied demographic factors, including the gender and ages of the farmers, and examined how these factors had correlated with farmers' adoption of Smart Farming in Vietnam. Among younger male farmers, a positive correlation with Smart Farming adoption was found. This study was consistent with [6], who found that the differences in gender, age, education level, and annual income of the farmers resulted in different ways of adopting Smart Farming. From the correlation of such studies, H1 has been employed:

H:1.1 Differences in gender result in different Smart Farming adoption.

H:1.2 Differences in age result in different Smart Farming adoption.

H:1.3 Differences in education result in different Smart Farming adoption.

H:1.4 Differences in income result in different Smart Farming adoption.

The concept of motivation: Motivation is the driving force that influences action to achieve a certain goal. It also dictates an individual's behavior and his or her direction. Individual motivation differs based on the factors that affect an individual. Two main factors are responsible for influencing the expression of behaviors: intrinsic and extrinsic motivations. Intrinsic motivation refers to one's consciousness and socio-psychological factors that drive behaviors and give rise to other factors. With intrinsic motivation, these factors are the key motivations that deeply influence the decision-making processes. Extrinsic motivation refers to the environmental factors that are comparably relevant to an individual's daily life activities. It is the main reason for decision-making. For example, in agriculture, intrinsic and extrinsic motivations have been influenced by the adoption of Smart Farming as follows [10]:

***Social motivation*:** [11] reported the definition of social motivation as an action or action taken by one or more people to alter other people's behaviors, thoughts, or feelings. More recently, in research by [12], the adoption behaviors of soil and water conservation technology were studied in the three provinces in China. The study found that social networks had been a factor that had positively influenced the farmers' adoption of soil and water conservation technology. The age of the farmers was also found to correlate with the perceptions of the adoption of soil and water conservation technology. Moreover, this was also consistent with findings from [13] on individual technology adoption and usage, which explained the factors involved with the farmers' use of technology. The study found that social motivation had affected the farmers' adoption and use of technology because the farmers felt that other farmers who had adopted and used technology had been prioritized over those who had not adopted the technology. Based on the correlation with such studies, H2 could be employed:

H2: Social motivation is positively correlated with Smart Farming adoption.

***Governmental support*:** A study by [7] examined the factors affecting the farmers' decisions to adopt organic farming in India. This study found that governmental support was the most important factor that could be implemented to convince farmers to adopt Smart Farming. It was also found that those farmers, who had not participated in training sponsored by the government, had been more likely to reject government-sponsored farming equipment. Furthermore, this is consistent with [14], who analyzed farmers who had rejected the technology of Smart Sorghum Cultivation in Tanzania. The results showed that farmers had alternately adopted the technology of Smart Sorghum Cultivation. In other words, they had adopted such technology in a short time. The key issue was shown to be a lack of serious and continuous promotion from the government.

Moreover, this is similar to findings from [15], who focused on the adoption of Smart Farming in the climate of the plains of Bihar in India. It was found that the government's financial assistance and modern agricultural equipment had positively affected the farmers' decisions to adopt Smart Farming. From the correlation of such studies, H3 could be employed:

H3: Governmental support is positively correlated with Smart Farming adoption.

***Relative benefits*:** The benefits derived from Smart Farming included ease of operation and the ability to receive large profits with little investment. A study by [16] revealed that farmers had focused on the relative benefits of Smart Farming when making their decisions to adopt Smart Farming. In line with a study conducted by [17], this study has focused on the benefits of Smart Farming adoption. Furthermore, it was found that the benefits derived from Smart Farming's technology had positively affected farmers' adoption of Smart Farming at a high level. From the correlation of such studies, H4 has been employed:

H4: The relative benefits of Smart Farming are positively correlated with Smart Farming adoption.

3. RESEARCH METHOD

The research population**:** Given that Northeastern Thailand is the region with the highest organic agriculture production, the studied population consisted of farmers from Northeastern Thailand [18].

The sample for this research**:** The selected farmers were required to be members of community enterprises in Northeastern Thailand. Moreover, they must have cultivated organic rice for more than one year. The sampling method was convenient sampling.

Sample size**:** This study was quantitative, and the population size was unknown. The computational method, which was based on Cochran's formula [19], was used to calculate the unknown sample size of the population. After making calculations using Cochran's formula, the author determined that the sample size for this research must be 400 farmers.

Measurement instrument**:** The data was collected using the field survey method, which employed a self-administered questionnaire for this research. The questionnaire was translated from English to Thai by language experts, and a back-translation process was used to re-translate the text into English to prevent any distortions in meaning [20].

The Index of Item-Objective Congruence (IOC) was used for content validity testing. In this process, the questionnaire was checked by three experts. The IOC was used to evaluate the questionnaire items based on the score range from -1 to +1. The items that had scored lower than 0.5 were revised. On the other hand, the items that had scores higher than or equal to 0.5 were reserved. This was found that the IOC values of all items were greater than 0.7, which supported the instrument's high validity. Moreover, confirmatory factor analysis (CFA) was used to test the construct validity. All constructs' factor loading was above the minimum recommended value (0.5) which also confirmed the high validity of the instrument [21].

The reliability of the questionnaire was determined to ensure that the responses collected through the instrument were reliable and consistent. The questionnaire was tested with 30 people that were not in the sample group. The reliability value was calculated using Cronbach's alpha to ensure internal consistency within the items [22], the value of Coefficient Cronbach’s Alpha must be at least 0.7 for accepted reliability. According to the questionnaire pre-test, Cronbach's Alpha coefficient of all parts are greater than 0.70, ranging from 0.746 to 0.982, which confirmed the highly reliability of the instrument [23].

The questionnaire**:** The questionnaire was designed for the respondents to complete by themselves (self-administered), and it was divided into 5 parts as follows: **Part 1** consisted of the respondents’ general information along with demographic characteristics [24, 25]; **Part 2** examined the respondents’ opinions towards social motivation [26]; **Part 3** explored their opinions about governmental support [27]; **Part 4** surveyed their opinions about the relative benefits of Smart Farming [28], and **Part 5** investigated their opinions about the adoption of Smart Farming [29].

Data analysis**:** The data derived from the self-administered questionnaires were processed using the SPSS Program to find the descriptive statistics, such as percentages, means, and standard deviations. For the hypotheses test, the data was analyzed using Structural Equation Model Analysis (SEM) to determine a demographic characteristics segment: gender, age, educational level, and income.

4. RESULTS

Demographic results: The majority of the respondents were females at 59.3%, with males at 40.8%. The age range of the majority was between 30-39 years old (33.6%), with an educational level of below a bachelor's degree (34.8%). Most had a total annual income that ranged between 100,001 - 300,000 baht (59.8%).

Hypotheses testing**:** For H:1.1-4, it was found that different genders, ages, educational levels, and annual incomes of the farmers had resulted in different adoptions of Smart Farming. The researcher divided the data into four segmentations of demographics: gender, age, educational level, and income, and then analyzed the data based on the hypotheses: social motivation, governmental support, and relative benefits. The results are described as table 1 in appendix.

Gender**:** The researcher divided the genders of the sample into 2 groups: males and females. The results indicated that the different genders had shown different adoptions of Smart Farming, which meant H1.1 could be accepted. The data clearly showed that the extrinsic motivation offered by governmental support had influenced males to adopt Smart Farming more frequently than females, with a factor loading of 0.772.

Age**:** The researcher divided the sample into three age groups: 20-40 years, 50-59 years, and 60 years and above. The results showed that the different ages had resulted in different adoptions of Smart Farming, which meant H1.2 could be accepted. The data showed that the extrinsic motivation in relative benefits was the highest factor that had influenced the farmers between the ages of 20-40 years to adopt Smart Farming with greater frequency than the other age groups and with a factor loading of 0.761.

Education**:** The researcher divided the respondents into two educational levels: 1) those individuals, who had received a level of education below a bachelor's degree, and 2) those who had received a bachelor's degree or above. The results indicated that the different educational levels had resulted in different adoptions of Smart Farming, meaning H1.3 could be accepted. The data showed that the extrinsic motivation in the factor of Social Motivation had been the highest factor. It had influenced those respondents, who had graduated with less than a bachelor's degree, to adopt Smart Farming more than those in the other educational level with a factor loading of 0.853.

***Income*:** The researcher divided the sample into three groups based on their annual incomes: 1) those earning below 100,000 baht, 2) those earning 100,001 - 300,000 baht, and 3) those earning more than 300,000 baht. The results showed that the different incomes levels had resulted in different adoptions of Smart Farming, meaning H1.4 could be accepted. The data showed that extrinsic motivation in the factor of governmental support had been the factor which had most greatly influenced the members of the sample, who were earning below 100,000 baht and had empowered them to adopt Smart Farming more than those at other annual income levels with a factor loading of 0.882.

To test the H2-4, the researcher next investigated the relationship between variables in the model, which can be analyzed using Structural Equation Modeling. As a result, it was found that the model showed the relationship between variables using the Maximum Likelihood estimation method by considering GFI between the model and empirical data. Furthermore, the results indicated that the relative model between the variables had been consistent with the empirical data and with the past statistical values, which is shown in the following table:

Table 2: The Structural Equation Model Test

Statistics	Measurements	Outcomes	Results
χ^2	-	2.145	-
df df	-	*2*	-
χ^2/ df	Less than 3.00	1.072	Passed
p	More than 0.05	0.056	Passed
CFI	More than 0.90	0.965	Passed
GFI	More than 0.90	0.923	Passed
RMSEA	More than 0.08	0.049	Passed
SRMR	More than 0.08	0.046	Passed

Note * $p < 0.05$ is statistically significant at 0.05

The results showed that χ^2 / df was equal to 2.41 and that the p-value of the model's variance matrix test and the empirical data were higher than 0.05 ($p > 0.05$). Therefore, the model and data had been consistent. According to an index of fit, the goodness of fit index (GFI) needed to be higher than 0.90, and in this case, the GFI had been 0.923, while the comparative fit index (CFI) had been 0.965. Conversely, the ideal value for residuals had to be less than 0.08, and in this case, the Root Mean Square Error of Approximation (RMSEA) was found to be 0.049, and the standardized root means squared residual (SRMR) had been 0.046. The results also showed that the SEM model had had a good fit with good reliability and validity and high factor loadings.

Table 3: The characteristics of relationships between variables

Measurement	Influence
H:1 Social motivation was positively correlated with Smart Farming adoption.	0.660
H:2 Governmental support was positively correlated with Smart Farming adoption.	0.853
H:3 The relative benefits of Smart Farming were positively correlated with Smart Farming adoption.	0.773

Note * $p < 0.05$ is statistically significant at 0.05.

The results showed that social motivation, governmental support, and the relative benefits of Smart Farming were the variables that had had a causal relationship with Smart Farming adoption. Moreover, governmental support was found to have had a strong influence on the adoption of Smart Farming. As a result, Smart Farming adoption was able to be predicted at 77.3% or R^2= 77.3. Consequently, all of the hypotheses could be accepted.

Table 3: The conclusions of the testing of the hypotheses

Hypotheses		Results
H1.1-1.4	The differences in demographic characteristics (i.e., gender, age, educational level, and annual income) result in different Smart Farming adoptions.	Accepted
H2	Social motivation was positively correlated with Smart Farming adoption.	Accepted
H3	Governmental support was positively correlated with Smart Farming adoption.	Accepted
H4	The relative benefits of Smart Farming were positively correlated with Smart Farming adoption.	Accepted

5. DISCUSSION

This research clarified the various factors impacting the farmers' adoption of Smart Farming and the different demographic characteristics, which had resulted in differences in Smart Farming adoption in Northeastern

Thailand. The study's findings have enabled us to effectively predict phenomena and their consequences and develop or improve the farmers' operational efficiency in Northeastern Thailand.

Social motivation had positively affected the adoption of Smart Farming among the females, aged 20-40 years old, who had an educational level of less than a bachelor's degree and who were earning below 100,000 baht annually. The social motivation was shown to be the strongest influence of extrinsic motivation for members of the sample who had graduated with a bachelor's degree or above with a factor loading of 88.5%. If the farmers had received support from others, such as family members, colleagues, or community leaders, then they would be convinced to adopt Smart Farming. These results were consistent with a previous study by [30], which studied soil and water conservation technology adoption. It was found that social networks were a factor that had positively influenced the farmers' adoption of soil and water conservation technology.

Governmental support was found to have positively affected the adoption of Smart Farming among those males ranging in age from 50-59 years, who had graduated with a bachelor's degree or above and who were earning below 100,000 baht. Governmental support was the strongest influence of extrinsic motivation in the sample, who were earning below 100,000 baht, with a factor loading of 89.3%. The results of this study were similar to previous studies conducted by [7], [14] and [15]. These studies focused on factors affecting the farmers' decisions to adopt organic farming. They found that governmental support had been the most important factor in convincing farmers to adopt organic farming. Furthermore, many farmers with governmental assistance had been able to continue their Smart Farming.

The relative benefits of Smart Farming were found to have positively influenced the adoption of Smart Farming among males between the ages of 20-40 years old, who had graduated with greater than a Bachelors' Degree and who were earning more than 300,000 baht. The relative benefits of Smart Farming were found to have the strongest influence of extrinsic motivation in the sample age range of 20-40 years, with a factor loading of 88.3%. This indicated that if the farmers' benefits from Smart Farming are adequate, then their adoption of Smart Farming techniques will positively increase. The result was consistent with findings from previous studies by [16] and [17], who examined the stimuli to empower small-scale farmers to adopt new farming techniques. Farmers focus on the relative benefits that they can receive from Smart Farming. The study also showed that the farmers are ready to accept Smart Farming because Smart Farming can increase the productivity of theirs farm.

6. CONCLUSION

From the research's findings, social motivation, governmental support, and the relative benefits of Smart Farming have influenced farmers to adopt Smart Farming in Northeastern Thailand. The most influential factor in adopting Smart Farming was found to be governmental support, followed by relative benefits and social motivation.

Furthermore, the differences in demographic characteristics had resulted in different adoptions of Smart farming in Northeastern Thailand. When the data from the demographic sample was categorized, the following was revealed: 1) those farmers, who had graduated with a bachelor's degree or above, must have the social motivation to adopt Smart Farming; 2) male farmers, who were earning below 100,000 baht, must have motivation in the form of government support to adopt Smart Farming, and 3) those farmers in the age range of 20-40 years old must perceive the relative benefits of Smart Farming in order to adopt Smart Farming.

7. SUGGESTIONS

Gender**:** This study found that governmental support was the highest extrinsic motivation that had influenced male farmers to adopt Smart Farming. Therefore, it is suggested that the government motivate male farmers and empower them to adopt Smart Farming by providing knowledge on Smart Farming techniques. In the beginning, the knowledge, to be imparted, should focus upon the use of small machinery to control irrigation systems and to replace human labor. Then the knowledge should be expanded and focus on the use of heavy machinery to create export products. The next stage of governmental support should consist of providing Smart Farming knowledge in production and transportation, which will help farmers control product quality, seed preparation, and soil accuracy.

Age**:** The study found that relative benefits were the highest extrinsic motivation factor influencing farmers between the ages of 20-40 years old to adopt Smart Farming. Therefore, the suggestion for motivating farmers between the ages of 20-40 years old to adopt Smart Farming is to create greater perceived relative benefits of Smart Farming. A Smart Agricultural Center for learning and training should be established for farmers interested in Smart Agriculture. This center could share knowledge, provide learning materials, and foster connections and cooperation in Smart Agriculture from the government, academia, the private sector, and the farmers themselves. This would enable farmers to realize the benefits of Smart Farming.

Education**:** The study found that social motivation is the highest extrinsic motivation that had influenced those farmers, who had graduated with less than a bachelor's degree to adopt Smart Farming. Therefore, the suggestion for motivating those farmers, who had graduated with less than a bachelor's degree, is to form groups of farmers, ask them to share their experiences in Smart Farming, exchange ideas, and persuade one another to carry out Smart Farming techniques. They may join with community leaders or local farmer networks to implement Smart Farming initiatives and inspire themselves and motivate their fellow farmers to turn to Smart Farming. When farmers talk to each other, they will gain confidence in adopting Smart Farming techniques because they will learn from their group members.

***Income*:** The study found that for those farmers, who were earning below 100,000 baht, governmental support had been the highest extrinsic motivation, which had influenced them to adopt Smart Farming. Therefore, it is suggested that the government should motivate the low-income farmers, who earn below 100,000 baht annually, to adopt Smart Farming by providing them with low-interest loans, which would allow them to invest in Smart Farming. This would create more opportunities for small-scale farmers to become Smart Farmers.

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APPENDIX

Table 1: The Factor Loading and AVE Analysis

Factors		Social Motivation		Government Support		Relative Benefits		Adoption Smart Farming	
		AVE	**Factor Loading**	**AVE**	**Factor Loading**	**AVE**	**Factor Loading**	**AVE**	**Factor Loading**
Gender	Male	0.78	0.684	0.66	0.865	0.58	0.786	0.62	0.772
	Female	0.69	0.856	0.59	0.741	0.63	0.774	0.56	0.652
Age	20-40 yrs.	0.71	0.764	0.80	0.696	0.75	0.883	0.59	0.761
	50-59 yrs.	0.82	0.752	0.74	0.791	0.72	0.799	0.69	0.723
	60 above	0.63	0.746	0.69	0.812	0.74	0.695	0.71	0.737
Education	Below bachelor's degree	0.64	0.885	0.64	0.874	0.76	0.752	0.75	0.853
	Above bachelor’s degree	0.69	0.867	0.59	0.774	0.75	0.876	0.68	0.768
Annual income	Below 100,000 baht	0.72	0.876	0.66	0.893	0.79	0.674	0.76	0.882
	100,001-300,000 baht	0.79	0.763	0.73	0.721	0.68	0.723	0.69	0.742
	Above 300,000	0.78	0.658	0.72	0.695	0.62	0.869	0.59	0.663