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Unified theory of acceptance and use of technology model to understand farmer's readiness: Implementation of precision agriculture based on digital IoT monitoring apps in West Java, Indonesia

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ABSTRACT
This research investigates the readiness of farmers in West Java to adopt IoT monitoring applications through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT) model. The digital transformation has introduced precision agriculture, an advanced technology-based approach that enhances the monitoring of crop and farmer needs. Smart farming leverages the Internet of Things (IoT) and sensor technology to optimize complex agricultural systems, thereby increasing productivity while mitigating environmental impact. Utilizing soil and weather sensors to measure temperature, nutrients, and humidity, the study explores factors such as performance expectancy, facilitating conditions, personal innovativeness, habit, behavioral intention, and use behavior that will influence technology adoption within diverse farming communities. A deeper exploration through the lens of the UTAUT Model reveals that West Javan Indonesian farmers are prepared to utilize the monitoring apps. The factors that affect the Use Behavior (UB) of the farmers consist of their internal or personal characteristics, Habit (H) and Personal Innovativeness (PI), and the external factors that correlate with the app developer's performance are Facilitating Condition (FC) and Performance Expectancy (PE). Habits from farmers for data recording and the personal innovativeness will increase the intention to use IoT monitoring apps.

Contribution/Originality: This study pioneers the application of the Unified Theory of Acceptance and Use of Technology (UTAUT) to evaluate farmers' readiness for precision agriculture using IoT monitoring apps in West Java, Indonesia. It integrates technology adoption theories with regional agricultural practices, offering innovative insights into digital transformation in farming.

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1. INTRODUCTION

Digital transformation has significantly impacted various sectors, including agriculture, where precision agriculture is a technology-based approach that monitors individual crop and farmer needs. This involves identifying and localizing crops, insects, and weeds, monitoring performance, and mapping plantings (Akhter & Sofi, 2022). Understanding the needs of smart farming is crucial for farmers to utilize data effectively. Smart farming uses technologies like IoT and sensors to optimise complex agricultural systems, increasing productivity and reducing environmental impact (Wicaksono, Suryani, & Hendrawan, 2022). IoT sensors help farmers identify specific field zones, reducing water use and chemical runoffs (Piramuthu, 2022).

In the modern agricultural landscape, the integration of technology has led to transformative shifts in farming practices, enabling greater precision, efficiency, and sustainability. Research on agricultural IoT technology is extensive and intensive, focusing on sensor extension (Xu, Gu, & Tian, 2022). Farmers' readiness to adopt digital technology is crucial for smart farming. Indonesia's telecommunications development has accelerated, raising agriculture's Gross Domestic Product (GDP) by 3.64%. However, digital familiarity doesn't guarantee effective IoT sensor usage. Communication tools and internet networks are necessary enabling conditions.

While existing research has often explored the barriers and facilitators of technology adoption in the farming sector, this paper offers a fresh perspective by comprehensively employing the interplay of 1) Performance Expectancy (PE), 2) Facilitating Condition (FC), 3) Habit (H), 4) Personal Innovativeness (PI), 5) Behavioral Intention (BI), and 6) Use Behavior (UB) of the UTAUT model. By delving into the intricacies of these multifaceted determinants, this paper contributes to a deeper understanding of obtaining the factors that influence the application of technology within diverse farming communities. In bridging the gap between theoretical insights and practical implementation, this research sheds light on novel pathways to foster precision agriculture development in an increasingly digital era.

This research aimed to understand the farmers' readiness to adopt IoT monitoring applications using a modified version of the Unified Theory of Acceptance and Use Technology (UTAUT) model to create precision agriculture. This paper addresses the question of how ready West Java farmers are to adopt monitoring applications and the internal and external factors that affect adoption readiness using the UTAUT Model. A key objective of the research is to study and gain insight into the factors influencing farmers' readiness to adopt Internet of Things monitoring applications in the context of precision agriculture.

2. LITERATURE REVIEW AND RESEARCH FRAMEWORK

2.1. Literature Review

The UTAUT2 model has been successful in assessing factors influencing technology acceptance of different technologies with high explanatory power (Walle, 2022). The extended UTAUT-3 model was modified to understand farmers' behavior in Indonesia, especially in West Java, regarding gadget usage. The authors eliminated four constructs because they were deemed irrelevant to the current behavior of West Java farmers, who have not yet utilized digital monitoring applications, and the IT company is still developing the product. The model can be modified based on the study's context (Venkatesh, Morris, Davis, & Davis, 2003).

Due to their lack of experience with digital monitoring IoT technology, farmers are unsure about its ease or pleasure of use. The IT company has not yet launched the product, developed a prototype, and decided on its price, making the farmers unaffected by significant constructs like SI. This uncertainty hinders their ability to influence the impact of digital monitoring apps on their operations.

Therefore, the model of UTAUT was modified based on the existing West Java farmers' behavior with six constructs as the latent variables:

2.1.1. Facilitating Condition (FC)

Facilitating Condition (FC) is a degree that represents the consumers' perceptions of the resources and support available to perform a behavior, such as the availability of technological resources and technical infrastructure. Several studies (Jahangir & Begum, 2008; Mital, Chang, Choudhary, Papa, & Pani, 2018; Sicari, Rizzardi, Grieco, & Coen-Porisini, 2015) have examined the effect of FC on consumers' perceived ease of use.

2.1.2. Performance Expectancy (PE)

Performance Expectancy (PE) is the measure of how effectively users can carry out specific tasks after adopting a technology (Venkatesh, Thong, & Xu, 2012).

2.1.3. Personal Innovativeness (PI)

Personal Innovativeness (PI) in this context of research is defined as an individual's perceived propensity or attitude that reflects their inclination to experiment independently with and adopt new developments in information technology (Schillewaert, Ahearne, Frambach, & Moenaert, 2005).

2.1.4. Habit (H)

Habit (H) can be defined as the extent to which people tend to perform behaviors automatically because of learning (Limayem, Hirt, & Cheung, 2007).

2.1.5. Behavioral Intention (BI)

Behavioral Intention (BI) is the motivational factor that influences a given behavior, and the stronger the intention to perform the behavior, the more likely the behavior will be performed.

2.1.6. Use Behavior (UB)

Use Behaviour (UB) can be defined as the degree of individual commitment to using specific technology continuously.

2.2. Research Framework

The research model proposed above was developed for a hypothesis based on West Java farmers' present behavior and various supporting ideas. The author's study hypothesis primarily concerns identifying technology adoption in West Java. The research-based hypotheses and their respective relationships: are listed below:

H_1: Facilitating conditions positively affect performance expectations.

Facilitative circumstances motivate customers to use technology more easily, such as in mobile shopping services, boosting performance expectations and enhancing the overall shopping experience.

H_2: Performance expectancy influences behavioural intention.

PE is the degree to which an individual believes that using technology would help them perform better in their work. PE has been identified as a component that influences BI. PE positively impacts the intention to use IoT technology (Ronaghi & Forouharfar, 2020).

H_3: Habit positively affects personal innovativeness.

The transfer of learning models can help establish mobile payment usage habits by highlighting the similarity between two inventions and personal innovativeness (Agarwal & Prasad, 1998). This helps identify individuals who are more likely to adopt IT advancements. Highly innovative customers are more likely to accept new technology when they consider it superior to incumbent innovations, even if it's technologically complicated and unfamiliar.

H_4: Personal innovativeness positively affects people's willingness to use digital IoT (UB).

PI is a human quality that impacts individuals' desire and openness to accepting new information technology innovations[11].

H_5: Behavioural intention positively influences the use behaviour of digital IoT systems.

A person's BI reveals their mental preparedness to be persuaded to use technology (Venkatesh et al., 2003). Furthermore, the Theory of Planned states that a higher degree of perceived behavioral control correlates with a higher intention to use technology. An individual's behavioral intention signifies their mental preparedness to adopt technology (Ronaghi & Forouharfar, 2020). Ultimately, the authors created a relationship between the original model and the best model of digital UB among Indonesian farmers, as shown in Figure 1.

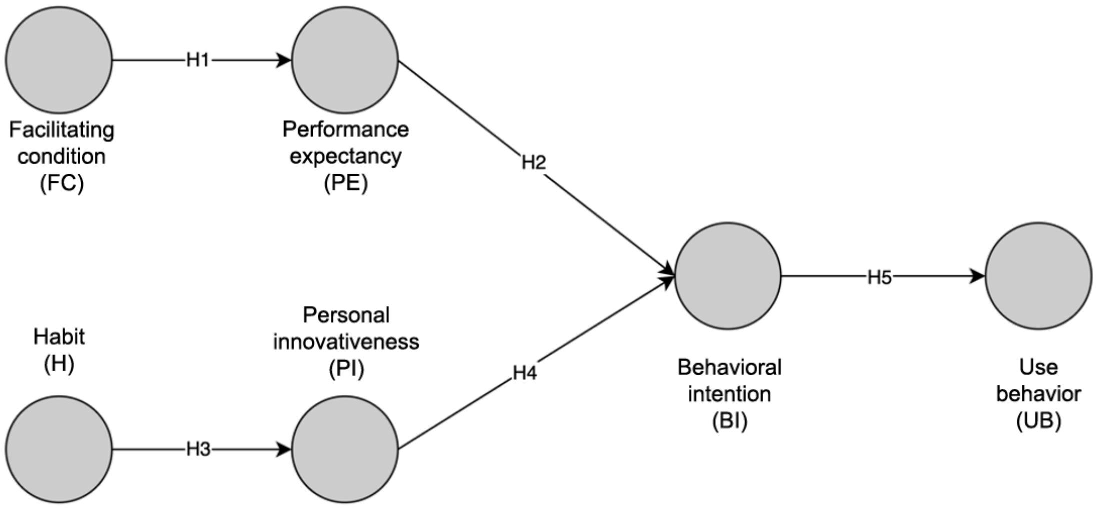

Figure 1. A proposed research model based on UTAUT for Indonesia farmers in West Java.

Source: Farooq et al. (2017).

The relation in Figure 1 was created specifically for this study. This research defines latent variables as a set of measurable variables that cannot be directly observed. These variables are inferred from the measured or observed variables, which are measurable and assigned to multiple questions to predict the latent variable in Figure 2. Therefore, the authors drew inspiration for the study's framework from Farooq et al. (2017) UTAUT-3. The theoretical framework proposed for this study can be seen in Figure 2.

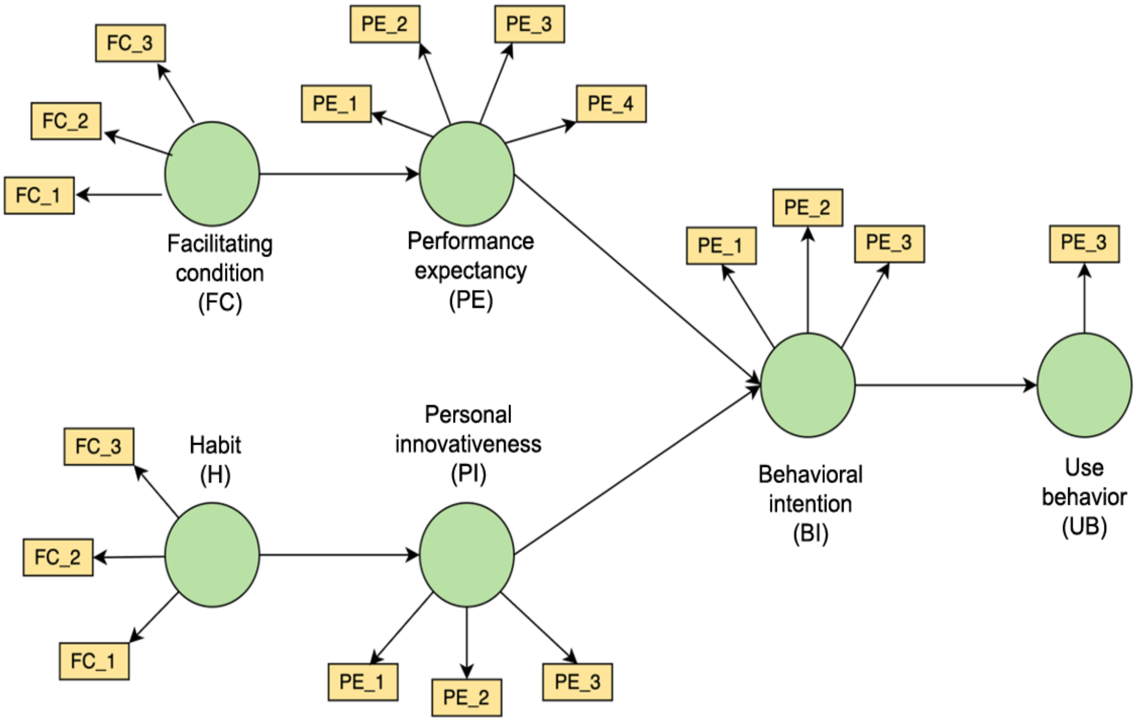

Figure 2. Proposed research model with questionnaire items based on UTAUT for Indonesian farmers in West Java.

3. METHODOLOGY

This study is conducted to understand the farmers' readiness to adopt IoT monitoring applications using a modified version of the UTAUT model. The proposed UTAUT model was validated through the quantitative method using surveys of 40 farmers in West Java. The primary products produced by the farmers who participated in the survey fall under the olericulture category. The farmers were chosen using a non-probability/non-random purposive sampling strategy to ensure they had prior experience with agriculture IoT devices, like weather and soil sensors; some of them were also the owners of the farm and could make the decision to adopt the technology. Non-probability purposive sampling, is a planned and focused strategy used in qualitative research to choose participants under the researcher's discretion who can give in-depth insights and information relevant to the research issue (Neuman, 2014).

The lack of details in empirical articles regarding the determination of sample sizes for SEM calculations often leaves the extent of sample-size planning unclear. Researchers frequently use rules of thumb, such as absolute minimum sample sizes or those based on model complexity. For SEM-PLS, a suitable sample size should meet one of two criteria: The sample size should be either (i) be at least ten times the largest number of items or questions used to measure a construct, or (ii) be ten times the largest number of paths associated with a construct. For the proposed UTAUT model, condition (i) requires a minimum sample size of 40 (Aparicio, Bacao, & Oliveira, 2016).

There are two parts to the quantitative data collection. The first part collects information regarding the demography of the farmers. The second part is a 5-point Likert scale questionnaire used to validate the UTAUT model using the structural equation modeling (SEM) calculation. This part consists of 19 questionnaire items, each serving as an observed variable that corresponds with the UTAUT-3 constructs or latent variables. The model and questionnaire items were retrieved from Farooq et al. (2017) with some adjustments to fit our objectives.

The data were analyzed using the Partial Least Squares (PLS) technique with SMARTPLS 3. Structural Equation Modeling (SEM) is a multivariate, hypothesis-driven technique based on a structural model representing hypotheses about causal relationships among variables (Stephan & Friston, 2009). Thus, to perform SEM-PLS, the UTAUT model must first be constructed according to the hypotheses concerning the relationships among variables.

4. RESULT AND DISCUSSION

4.1. Demographic Summary Result

This study collected some demographic data to get the depiction of the respondents. Table 1 presents the summary of the data collected in the study.

Table 1. Demographic information for questionnaire respondents.

Characteristics	n (Respondents)	%
Gender		
Male	20	50
Female	20	50
Age		
< 25 years old	2	5
25-45 years old	18	45
> 45 years old	20	50
Last education		
No formal education	2	5
Primary school	21	52.5
Junior high school	7	17.5
Senior high school & equivalent	6	15
Diploma & bachelor degree	4	10
Years of farming experience		
< 5 years	9	22.5
5-10 years	6	15
10-20 years	16	40
>20 years	9	22.5
Total land area		
<1000m2	6	15
1000-5000m2	8	20
5000-10000m2	2	5
>10000m2	5	12.5
Electric device ownership		
Feature phone (SMS & call only)	8	20
Smartphone - Android	20	50
Smartphone - Apple	2	5
Laptop/PC	3	7.5
No device	11	27.5

The table reveals that many farmers, irrespective of their digital skills, share their devices with the family members such as children or partners. Many farmers, regardless of their digital skills, share their devices with family members, bridging the digital divide.

The importance of digital access, particularly for those with lower literacy, motivates this practice. Farmers typically start their work in farming from primary school, with most relying on instinct and sense rather than data for farming activities.

4.2. SEM – PLS Calculation Result

All calculations for SEM-PLS were processed using SmartPLS 3.0. To ensure the reliability and validity of the questionnaire items, construct validity and reliability tests were conducted by assessing Cronbach's alpha (CA), average variance extracted (AVE), and composite reliability (CR). CA and CR measure the internal consistency of the questionnaire's scale, while AVE evaluates the proportion of variance captured by a construct relative to measurement error. For the model to be considered reliable, CA and CR values should exceed 0.7, and the AVE should be above 0.5.

Table 2's reliability test result shows that all constructs have values of 0.7 and above for CA and CR, demonstrating the consistency of the questionnaire's scale.

Table 2. Construct validity and reliability.

Variable	CA	CR	AVE
BI	0.823	0.894	0.739
FC	0.813	0.878	0.648
H	0.856	0.912	0.775
PE	0.892	0.925	0.757
PI	0.773	0.869	0.689
UB	1.000	1.000	1.000

The discriminant validity of the proposed model was assessed using the Fornell-Larcker criterion, which requires that the square root of the Average Variance Extracted (AVE) for each construct be higher than the highest correlation between that construct and any other construct in the model.

The Fornell-Larcker criterion calculations for the proposed model are presented in Table 3, and the results meet the required standard.

Table 3. Calculatioin of the Fornell-Larcker criterion for the discriminant validity.

Variable	BI	FC	H	PE	PI	UB
BI	0.859					
FC	0.650	0.805				
H	0.440	0.747	0.880			
PE	0.735	0.712	0.436	0.870		
PI	0.736	0.833	0.790	0.722	0.830	
UB	0.556	0.661	0.515	0.417	0.663	1.000

The study used 19 questionnaire items as observed variables to explain latent constructs' value. The outer loading of these variables determined an item's absolute contribution to its assigned construct. H_4 and FC_4 were found to be negative, indicating their contribution was insignificant and removed from the proposed model.

4.3. Hypothesis Result

The P-value and path coefficient were calculated using the new proposed model, determining the significance of constructs in the relationship. A P-value less than 0.05 rejects the null hypothesis, while the path coefficient explains the direct effect of constructs. The P- value and path coefficient for the hypotheses mentioned in the research framework are shown with the proposed model in Figure 3.

The hypothesis testing resulted in p-values of all relationships being below 0.05 (0.000 for H1 (FC → PE), H2 (PE → BI), and H3 (H → PI), 0.009 for H4 (PI → BI), and 0.003 for H5 (BI → UB)), indicating that all the relationships are significant, thus the hypotheses are accepted.

Figure 3 shows the final model, the external loading of each variable to each construct, and the path coefficient of each construct's relationship.

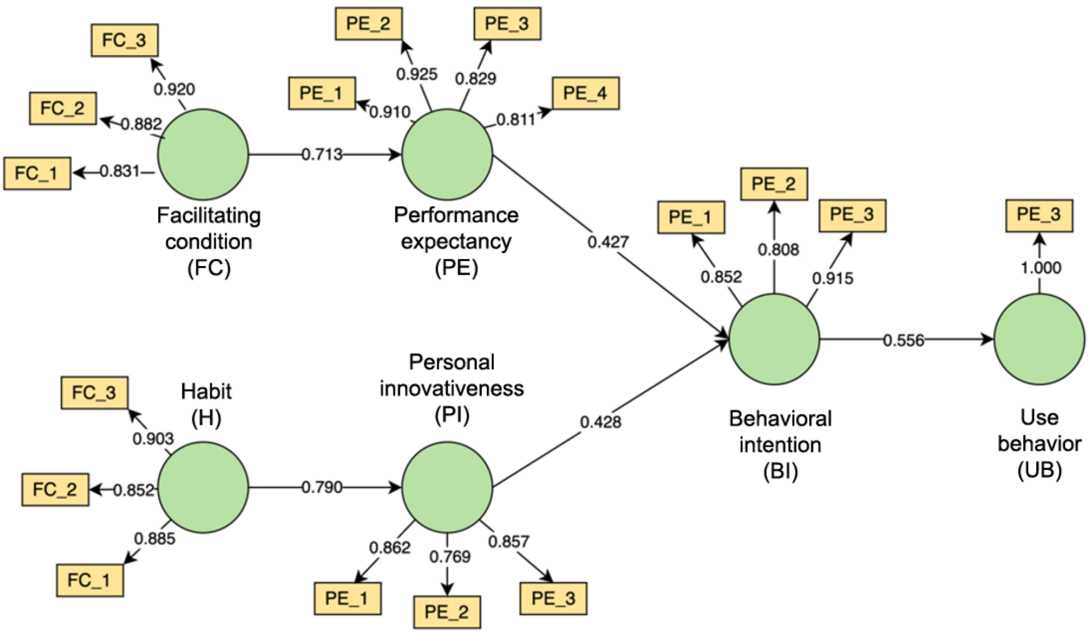

Figure 3. UTAUT model for West Java farmer.

The highest path coefficient value is observed between H and PI (H3) (0.790), suggesting that H strongly affects PI.

5. CONCLUSION

In summary, after considering several factors, it is clear that the Indonesian farmers in West Java are ready to use the monitoring apps. The factors that affect the UB of the farmers consist of their internal or personal characteristics (H and PI) and external factors that correlate with the app developer's performance (FC and PE).

The results show that if the farmers perceive the FC to be in an ideal condition, this will help farmers create the PE to carry out specific tasks after adopting a technology (Venkatesh et al., 2012; Venkatesh, 2003) which will affect their intention to use the UB. Further, H had the highest path coefficient value, strongly affecting PI. Thus, creating a way for the farmers to develop a habit of recording agricultural data will help them carry out specific tasks after adopting a technology (Venkatesh et al., 2012; Venkatesh, 2003). Once farmers develop the habit of recording agricultural data, their use of the technology will increase, leading to an increase in their intention to use it, which in turn positively impacts the User Base (UB) of digital IoT monitoring apps.

6. LIMITATION AND FUTURE RESEARCH

This study used a purposive sampling strategy due to the limitations of knowing the exact number of farmers who are familiar with or already use IoT monitoring apps and cross-sectional design, so there is limited scope to gather data only on farmers in West Java who were exposed to agriculture IoT sensors. Future research could incorporate some case-study-related variables into the UTAUT. Further, to make this research more comprehensive, the authors also suggested that future researchers continue this study by adding user acceptance testing (UAT) to obtain an in-depth understanding and gather the farmer's feedback after launching the digital IoT monitoring apps.

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Transparency: The authors state that the manuscript is honest, truthful, and transparent, that no key aspects of the investigation have been omitted, and that any differences from the study as planned have been clarified. This study followed all writing ethics.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Study conception and design, N.L, A.A.P., A.S.S., N.A. and O.S.S.; data collection, A.A.P., A.S.S., N.A. and O.S.S.; analysis and interpretation of results, A.S.S. and N.L.; draft manuscript preparation, N.A., A.A.P. and O.S.S. All authors have read and agreed to the published version of the manuscript.

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APPENDIX

Appendix A Presents a list of research questions that adopt the UTAUT model to assess farmers' readiness for the implementation of precision agriculture based on digital IoT monitoring apps in West Java, Indonesia.

Appendix A. List of research question.

Variables	Code	Question
Farmers identity		1. Name
		2. Age
		3. Gender
		4. Education background
		5. Time of farming experience (In year)
		6. Commodity
		7. Land area size (m2 or hectare)
		8. Ownership of electronic devices
Agricultural data recording habits		1. Are you used to recording agricultural data?
		2. Reasons for doing or not recording agricultural data?
		3. What data is usually recorded?
		4. How frequently is agricultural data recorded?
		5. If there is a digital application to help farmers record data, would you be interested? (Yes/No) Please state the reason
Performance expectancy (PE)	PE_1	Digital IoT monitoring apps are very useful for my farming activities
	PE_2	Digital IoT monitoring apps help me to complete farming activities better
	PE_3	Using digital IoT monitoring apps increases the productivity of my farming activities
	PE_4	Using digital IoT monitoring apps helps me to produce better yields
Facilitating conditions (FC)	FC_1	I have a laptop to use digital IoT monitoring apps
	FC_2	I know how to use digital IoT monitoring apps
	FC_3	The digital IoT monitoring apps in my farmer group can be operated via my cell phone
	FC_4	The digital IoT monitoring apps provider provides assistance facilities when I encounter problems in its use
Habit (H)	H_1	I often use/Read graphs displayed in digital IoT monitoring applications
	H_2	I am used to using digital IoT monitoring applications
	H_3	The use of digital IoT monitoring applications has become a habit for me
	H_4	I am used to recording my agricultural activities manually in a notebook
Personal innovativeness (PI)	PI_1	I like to try new features and developments in the world of information technology
	PI_2	I am interested in trying the new features found in the digital IoT monitoring application
	PI_3	Usually, I am one of the first to adopt the latest monitoring applications among my colleagues
Behavioral intention (BI)	BI_1	I am interested in using digital IoT monitoring applications on my farm in the future
	BI_2	I will provide recommendations to other farmers to use IoT monitoring applications on their farms
	BI_3	I have positive expectations for my farm, when I use IoT monitoring applications
Use behavior (UB)	UB_1	How often will I use IoT monitoring applications on my farm