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Are Farmers Ready to Switch Using Precision Agriculture

Andi Wiliam[1], Mts Arief[1], Agustinus Bandur[1], Viany Utami Tjhin [2]

[1] Management Department, BINUS Business School Doctor of Research in Management, Bina Nusantara University, Jakarta, Indonesia 11480,

[2] Information Systems Management Department, BINUS Graduate Program – Master of Information Systems Management, Bina Nusantara University, Jakarta, Indonesia 11480

andi.wiliam001@binus.ac.id

Abstract. Smart farming-related innovative technologies are anticipated to have a substantial impact on the capacity of agriculture to adapt to climate change and sustainable farming. The acceptance of farmers, and specifically the use of smart products, is essential for the implementation of smart agricultural solutions. Because of this, it is critical to comprehend the factors that affect farmers' decisions to use these technologies. Farmers in West Sumatera, Indonesia, were questioned by way of an online survey in 2021 (n = 299) to fill this knowledge gap. On the basis of an enlarged version of the Unified Theory of Acceptance and Use of Technology (UTAUT), a Partial Least Squares (PLS) analysis was conducted. According to the findings, farmers' intentions to employ smart products are significantly influenced by performance expectations, effort expectations, and social influence. Additionally, the facilitating condition has an impact on how the farmers really use their technology. The novelty component in this study, government social power, also affects real use behavior. Farm size did not appear to have a moderating effect on farmers' propensity to utilize smart products, though. The study can aid in the development of strategies for specialized technical solutions that address farmers' needs and has significant management implications for technology businesses working in the field of smart farming. This paper identifies key factors that will enable farmers to not only become able to adapt to the technology, but also to sustain agriculture.

Keywords: UTAUT, technology adoption, precision agriculture, management information system.

1. Introduction

Agriculture has long been plagued by issues with food security, food safety, sustainable development, and health, especially in developing countries like Indonesia (Workie et al., 2020; Wiliam et al., 2021). One of the most significant efforts undertaken by agricultural organizations to provide information to farmers in an effort to increase their productivity and well-being is agricultural development in general (John & Babu, 2021). Agricultural development is a type of informal education that offers guidance through educational activities who need it or who are experiencing socioeconomic challenges so they can expand their knowledge and abilities (Zahra, 2018).

Due to the speedy development of communication technologies, many people have altered their methods of information gathering to be more inventive, quick, and engaging, regardless of time or location (Dwivedi et al., 2021). The majority of farmers continue to use traditional media outlets and interpersonal communication to get information on paddy planting operations, from the leveling off the ground to the harvesting process (Rahman et al., 2020). This is especially true of paddy plantation-related activities. Given that rice is the nation's primary grain, it is essential that farmers receive this information in order to ensure a strong harvest and good quality. Thus, in order to increase their plantation and output, farmers must heavily rely on innovation-integrated communication channels.

Smart industrial agriculture was transformed by the use of technology, which also had an impact on how efficiently it used available resources, both economic and natural (Ronaghi & Foroufarfar, 2020). The Internet's prospective uses have been dramatically changed by the technology's user-friendly features. Adoption of a new technology is the first phase of its use (Straub, 2017). The decision-making processes could be developed and optimized after the users use the technology (Van Deursen & Mossberger, 2018). Thus, the question of whether huge, industrial farms will be the only ones with access to the newest technologies arises.

Meanwhile, the majority of technological challenges are evident on the ground and in real-world settings, demonstrating either their technological robustness or, conversely, their impotence. In earlier research, the application of technology in precision agriculture has received more attention. For instance, Khanna and Kaur (2019) thoroughly investigated the scholarly efforts in technology acquisition for Precision Agriculture (PA). They evaluated the extent to which each significant researcher and each university contributed to the PA literature.

From compliance-based viewpoints, academics have described how social influence modifies a person's cognition, attitude, or conduct (Raven, 1964). One important component of social influence connected to one's intellectual activity in organizations has been identified as social powerFocusing on social power can help us understand how and why people unintentionally exploit knowledge resources in practice. However, little is known about how social influence may affect how knowledge is used.

In the context of Indonesian agriculture, this study would like to demonstrate that the application of combining a model for investigating the acceptance of technologies (for example, UTAUT) with the addition of several other factors can make a different contribution in decision making. This study seeks to fill the research gap by looking into the factors embedded in the UTAUT theory which provided a framework to determine an understanding of the farmers' behavioral intention and use of smart devices with the addition of governmental social power and farm size as the moderators. The factors can be found in order to better comprehend how farmers' behavioral intentions and use of smart products are influenced and how adoption may be encouraged.

2. Literature Review

We begin by giving a succinct outline of the unified theory of acceptance and usage of technology in this section (UTAUT). We then introduce the background of social power and later describe the views on precision agriculture.

2.1. UTAUT

This study used the Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), to better understand farmers' adoption decisions. The UTAUT takes into account the behavioral variables expected performance (PE), expected effort (EE), social norm (SN), and facilitating conditions (FC).

The degree to which a person believes that employing technology makes a task easier to accomplish or improves his or her performance at work is known as Performance Expectancy (PE) in the UTAUT. As a result, the theory predicts that PE will have a favorable impact on people's behavioral intentions (BI) to use technology (Venkatesh et al., 2003). As a result, the theory predicts that PE will have a favorable impact on people's behavioral intentions (BI) to use technology. The definition of effort expectancy (EE), which is thought to have a favorable impact on BI, is the degree of comfort a person connects with using a system (Venkatesh et al. 2003). Information that is readily available should be simple to comprehend and delivered right away (Rose et al., 2016). The perceived utility of a technology increases with ease of use. According to Venkatesh et al.'s (2003) definition, social norm (SN) refers to the degree to which a person thinks that significant people in their immediate environment think that he or she should use a new technology. Ambrosius et al. (2015) and Schaak and Musshoff (2018) both demonstrated the influence of other farmers on farm decisions. Venkatesh et al. (2003) define facilitating conditions (FC) as the extent to which a person believes that the current technical infrastructure facilitates the usage of the relevant technology. FC are thought to directly affect the adoption choice. According to Michels et al. (2020), the adoption of smartphones may be constrained by limited mobile internet coverage. Some of these apps might need mobile internet connectivity to identify weeds or acquire weather updates, much like how some crop protection smartphone apps may need it to access databases. More crucially, crop protection smartphone apps must be able to be installed on the phone itself. Understanding the behavioral elements that affect farmers' adoption choices can assist to explain and forecast farmers' use of crop protection apps and direct future development.

2.2. Social power

The authors used the traits of expert power, referent power, legal power, coercive power, and reward power from Hinkin and Schriesheim's social power model to create the current study model. Based on the social power model, we contend that the five bases of social power have a variety of effects on a person's affect and PTMS. According to French and Raven, these five power bases can be translated into three different kinds of social power. Legitimate power is characterized as power through authority, whereas coercive power, reward power, and legitimate power are all described as power through control. Power through persuasion is a term used to describe expert power, referent power, and influence power.

Legitimate authority is based on a pre-existing standard or norm that the partner expressing power acknowledges (Hofmann et al., 2017). This point of view presupposes that the spouse recognizes the actor's right to defend their stance. A person in such a position is legally able to order their spouse to act in a certain way, and the partner will be under obligation to comply. Most people think that authority is just and fair. People are impelled to uphold and protect the social institutions that are in place (Resnik & Elliott, 2016). They maintain social hierarchies even when it is not necessary. People like to think that the rightful decision-makers determining their fate are fair (Lee et al., 2019).

Their interpretation of the actors' qualities is positively distorted by this point of view (Stevens & Fiske, 2000).

People prefer to think that an authority figure has virtues when they are connected to it. There is frequently an institutionalized mutual between team members. It is the institution's duty to promote this trust. Consequently, people must have more faith and confidence in a legal power. Partners are happier with outcomes from legitimate authority since outcomes are viewed as being more favorable.

2.3. Precision agriculture

Utilizing cutting-edge technology, integrated and sustainable farm management practices use precision agriculture to boost farm profitability by minimizing negative environmental effects and labor costs (Mokariya & Malam, 2020). In addition, precision agriculture is also expected to reduce the use of inputs and thereby reduce negative external environmental factors in the adoption of technology (Ammann et al., 2022). Precision agriculture technology is not only the addition of new technology but is an information revolution, made possible by new technologies responding at a higher level, management systems. more precise agriculture by utilizing Internet-of-Things (IoT) technology. Precision agriculture can send and receive real-time data from sensors and artificial intelligence systems (Shin et al., 2022). Through precision agriculture, farmers can measure land such as air, soil, temperature, and so on. With these variables, farmers get information for pesticide treatment, fertilization, irrigation, and so on so that good planning can be done in farming productivity (Pedersen & Lind, 2017).

Previous studies have concentrated on the widespread use of smartphones and farmers' willingness to pay for crop protection apps. This study uses the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine latent factors that affect farmers' decisions to employ smartphone crop protection applications (Michels et al., 2020). According to the descriptive findings, although 95% of the farmers polled use smartphones, only 71% of them also utilize crop-protection apps.

The majority of farmers think that apps that offer information on weather forecasting, pest scouting, and investing are the most valuable. The reported uses, however, are lower than the stated uses. The behavioral intention to use smartphone applications varied by 73% according to the UTAUT model (Michels et al., 2020). Several other studies examined the adoption of technology to use text messages known as Short Message Service (SMS) based on UTAUT (Beza et al., 2018). Furthermore, the results of this study are the results from the individual point of view and not the characteristics of the company. The questions given to the theoretical level differ greatly between individuals and companies (Li, 2020)

3. Hypothesis Development

The following section discusses how intention to use technology is associated with its predicators (i.e., performance expectancy, effort expectancy, and social influence), use behavior with its predicators (i.e., intention to use, facilitating condition, and government social power). Also discussed are the connections in the suggested model (see Figure 1). The constructs used in the model are reviewed briefly before presenting the hypotheses.

3.1. Performance expectancy and intention to use technology

Performance expectancy measures how strongly a person thinks employing a system or piece of technology will be advantageous, provide support, and provide them a comparative advantage (Venkatesh et al., 2003). Economic success has a significant impact on how quickly new technologies or methods are adopted in agriculture (Wolfert et al., 2017). Economic factors are reportedly one of the main forces behind farmers' adoption of smart agricultural technologies (Walter et al., 2017). A further advantage of smart products is their potential to contribute to a more sustainable agriculture in the framework of smart farming. This conversation enables us to state the following claim:

Hypothesis 1: Expected performance is associated with technology usage intention.

3.2. Effort expectancy and intention to use technology

The predicted effort of utilizing a system or piece of technology is known as the effort expectation, and it is frequently believed that the initial effort will be higher for new systems. The anticipated effort comprises both time and money commitments. Instead of the use itself, learning how to utilize and run a system or piece of technology is generally connected with additional labour (Rose et al., 2016). The discussion allows us to formulate the following hypothesis:

Hypothesis 2: Expected effort is associated with intention to use technology.

3.3. Social influence and technology usage intention

Social influence is the result of significant individuals, such as friends, coworkers, and relatives, who persuade someone to use a technology or system (Moussaid et al., 2013). The influence of politics or the media on society is also taken into account. A study that looked at how co-workers, friends, and family influenced strategic agricultural decisions found that social factors played a role in matters like corporate growth, sustainable agriculture, and conservation techniques (Kuzcera, 2006). A farm’s operational development is somewhat influenced by the social environment, including friends and family (Foster & Rosenzweig, 1995). Additionally, it has been discovered that a farmer’s future use of new technologies is significantly influenced by their colleagues’ experiences with them (Bahner, 1995). The discussion allows us to formulate the following hypothesis:

Hypothesis 3: Social influence is associated with intention to use technology.

3.4. Facilitating condition and use behavior

The concept of facilitating conditions identifies the extent to which respondents think that a farm’s organizational and technological infrastructure supports the utilization of the system. Thus, the idea of facilitating conditions includes all of the operational requirements that make it possible to employ smart devices in the first place. The adoption itself as well as the use behavior are both impacted by the facilitative environment (Popova & Zagulova, 2022). The discussion allows us to come up with the following hypothesis:

Hypothesis 4: Facilitating condition is associated with intention to use technology.

3.5. Government social power and use behavior

Government social power bases include government coercive power, government legitimate power, government referent power, and government expert power (Lu et al., 2014). Farmers believe that government agencies that support adoption have some useful experience or comprehension on the agricultural information system. Expert stakeholders are regarded as reliable, which intensifies their pull on farmers' usage intentions (Biong et al., 2010). Farmers accept the policymaker's recommendation when they believe it has competence because they think doing so would result in a better conclusion. Government legitimate power is the belief that a stakeholder has the authority to order a specific behavior for other participants (Mitchell et al., 1997). A farmer must give in to the government's influence because they believe they have a right to do so. This is the foundation of legitimate authority. Referent power indicates that the government supports farmers' interests. In order to give farmers information and services, the government supports agricultural information systems. Farmers will understandably think that the government is on their side if they find the information to be relevant to their requirements. As a result, farmers will be open to the information system from the perspective of social commerce (Valentine, 2009). Farmers' perception of the government's ability to offer incentives to encourage the adoption of information systems is referred to as the government's reward power. More particular, farmers who use information systems benefit more from government and commercial information services. The government can thus promote a mindset among farmers where they believe that the reward power mechanism will motivate them to use an information system (Stevens et al., 2005). When someone believes that the government has the power to punish them, they are said to have government coercive power. Based on their unique demands, farmers purchase information services developed by the government. According to Gundlach and Cadotte (1994), an unbalanced and antagonistic buyer-seller relationship is related to coercive power. Coercive power will therefore be detrimental to the buyer-seller relationship. The discussion allows us to come up with the following hypothesis:

Hypothesis 5: Government social power is associated with intention to use technology.

3.6. Farm size and intention to use technology

According to Sheng et al. (2016), the size of the farm positively correlates with the performance of the entire farm. As a result of scale economies, variances in productivity, market prices for inputs, and the transaction costs connected to evaluating and acquiring new technologies, small farms frequently lag behind bigger farms (Perrin & Winkelmann, 1976). The relationship between predicted effort and intention is therefore believed to be moderated by farm size. The discussion allows us to formulate the following hypotheses:

Hypothesis 6: The relationship between expected performance and intention to adopt technology is influenced by farm size.

Hypothesis 7: The association of expected effort and intention to adopt technology is influenced by farm size.

Hypothesis 8: The association of social influence and intention to adopt technology is influenced by farm size.

3.7. Intention to use technology and use behavior

Behavioral intention includes having or not having plans to use smart devices. It shows farmers' views toward smart products with some moderator influence on the strength of the relationships between the independent variables and behavioral intention. It is anticipated that behavioral intention will have a substantial favorable impact on how people use technology (Venkatesh et al., 2003). The discussion allows us to formulate the following hypothesis:

Hypothesis 9: Intention to use technology is associated with use behavior.

4. Methodology

In this study, the type of probability sampling used was cluster random sampling. The population of farmers using technology is taken from those who reside in West Sumatera, with a total population of 1,320 (54.95%) users, to represent Indonesia (see Table 1). Next, data collection was carried out randomly based on data taken from Kominfo (Ministry of Communication and Information Technology) website. The types of farmers studied are based on those who have used precision agricultural technology to get the harvest.

From June to September 2021, this research was completed, beginning with preparation, data collection, processing, and analysis. To increase the number of responses, the researchers used an online survey platform that included 4-Likert Scale items and delivered the survey to participants online. Farmers who have been using smart apps as communication tools are specifically targeted by the responses. Online messengers like WhatsApp and Google Form were used to distribute the questionnaire and collect the results. The results of the questionnaire serve as the study's core research data. The questionnaire will immediately provide the research's appropriate criterion respondents. Survey options on the actual questionnaire range from (1) Strongly Disagree to (4) Strongly Agree.

Table 1: Population of farmers using precision agricultural technology.

Province	Commodity	# of Farmers	%
West Sumatera	rice, corn, red pepper	1,320	54.95
West Java	rice, corn, red pepper, sweet potato, ground nut, curcuma	370	15.40
East Java	rice, corn, red pepper, onion	310	12.91
Central Java	rice, ground nut	181	7.54
North Sumatera	rice	79	3.29
Yogyakarta	rice	69	2.87
West Nusa Tenggara	corn	38	1.58
Riau	garlic	24	1.00
North Sulawesi	rice	11	0.46

By gauging the participants' agreement with seven survey questions from Schukat and Heise, we were able to determine performance expectations (2021). Here are a few examples: (1) By using smart products, I can avoid performing some tasks; (2) By using smart products, I can reduce the time needed to complete some tasks; and (3) I can speed up routine tasks on my farm by utilizing smart products. Five factors make up Schukat and Heise's (2021) measurement of effort expectancy: (1) I think handling smart products will be challenging; (2) I find it challenging to learn how to utilize smart products; (3) I find managing smart products safely to be challenging. Items taken from Schukat and Heise (2021) were used in this study to measure the four dimensions of social influence, including: (1) I believe using smart products on my farm is well-liked by my coworkers; (2) I believe using smart products makes a good impression on society; and (3) The people in my social circle—neighbors, coworkers, and friends—support my decision to use smart farming equipment. Seven criteria make up Schukat and Heise's (2021) measurement of the facilitating condition, including (1) I am fully technologically capable of making focused use of smart items; and (2) The entire farm has access to the internet or a mobile internet connection. Eight survey questions are used to measure government social power, according to Lu et al. (2014). These include the statements: (1) The government might inflict harm on anyone who disobey its regulations; (2) I must use Information Village because of the advantages it will bring; and (3) Because I am a farmer, my mindset is similar to that of the government; (4) I am obligated to follow government instructions, the officer has a lot of information, and (5) I usually know what is best for my agricultural productivity. The five elements in Schukat and Heise's (2021) measurement of technological intention include (1) I would immediately use smart items on my farm, and (2) I want to use them there soon. The six components that make up Schukat and Heise's (2021) measurement of usage behavior include: (1) a smartphone to keep track of or manage operational components like machinery or farm equipment, as well as to fulfill documentation needs or recruit staff (operational purposes other than telephoning or other communication).

5. Results and Discussion

The PLS-SEM method, commonly known as partial least squares structural equation modeling, is used in this work to analyze data, is a two-step procedure that entails both evaluation measurements and structural models. First is to test the composite reliability (CR), a score that will measure the construct's latent variables. To be regarded appropriate, the CR must be 0.7 or higher (Hair et al. 2017a). The average variance extracted (AVE) scores of all constructs likewise met the 0.5 threshold, implying high convergent validity (Hair et al. 2017b).

Table 1 shows that the α coefficient of performance expectancy, effort expectancy, social influence, facilitating condition, government social power, intention to use technology, use behavior, and farm size are 0.842, 0.787, 0.739, 0.809, 0.835, 0.742, 0.751, and 1.000, respectively. Those values indicate that all variables are reliable since those value exceed the minimum threshold of 0.7 (Hidayat et al. 2021). All values are higher than the threshold of Cronbach's Alpha which is 0.7, meaning that all constructs are fundamentally consistent and reliable variables to use in this study.

Meanwhile, performance expectancy, effort expectancy, social influence, facilitating condition, government social power, intention to use technology, use behavior, and farm size have AVE values of 0.718, 0.583, 0.539, 0.613, 0.547, 0.625, 0.574, and 1.000, respectively, as presented in Table 2. Since the AVE values meet the minimum threshold of 0.5, it indicates that all variables are accurate and valid (Hair et al., 2014). Therefore, employee engagement, role benefit, and innovative behavior are fundamentally accurate and valid variables to employ in this study.

Table 2: Internal consistency (Alpha, CR, and AVE).

Construct	Alpha	CR	AVE
Expected Performance	0.842	0.884	0.718
Expected Effort	0.787	0.840	0.583
Social Influence	0.739	0.847	0.539
Facilitating Condition	0.809	0.882	0.613
Gov't Social Power	0.835	0.827	0.547
Intention to Use Technology	0.742	0.887	0.625
Use Behavior	0.751	0.836	0.574
Farm Size	1.000	1.000	1.000

Table 3 shows that the R^2 in "Intention to Use Technology" is 0.171, barely above 0.1, indicating a weak linear connection value. This study used R^2 Adjusted to determine the effect because it corrected on the standard error value and gives a more robust picture than R^2 (Bell et al., 2019). In this construct, the adjusted R^2 is 0.158, indicating that 15.8% of the dependent variable (intention to use technology) can be described through the independent variables (performance expectancy, effort expectancy, social influence). In the next construct, the adjusted R^2 is 0.319, showing a moderate relationship of "Use Behavior" that can be described through the independent variables (facilitating condition, intention to use technology, government social power).

Table 3: Model summary.

Construct	R^2	Adjusted R^2
Technology Usage Intention	0.171	0.158
Usage Behavior	0.324	0.319

The results of an initial structural model analysis suggested that there was no collinearity at the critical level. The output of the PLS algorithm's computation of the route coefficients is shown in Table 4 and Figure 1.

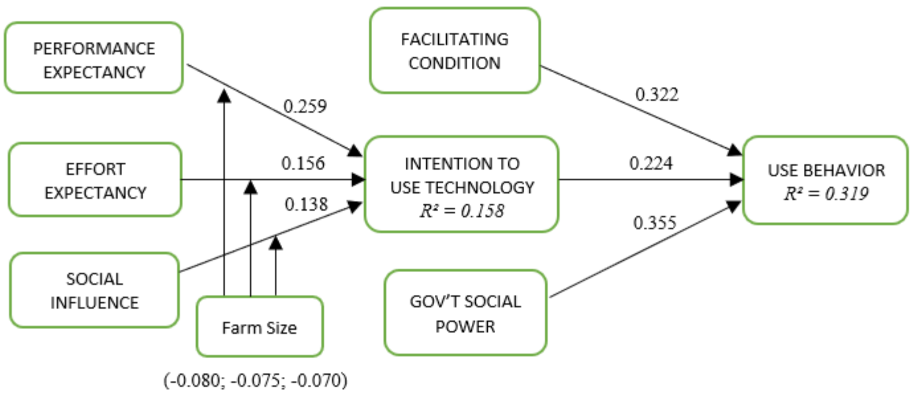

Fig 1: Results of the PLS analysis.

The direct effect of expected performance on technology usage intention appears to be positive and significant (β = 0.171/t = 3.960). Thus, *H1* is supported, as economic benefits have a significant impact on how quickly smart products or methods are adopted in agriculture. The results are also supported by past studies, e.g., Walter et al. (2017).

As proposed in *H2*, expected effort is positively associated with technology usage intention (β = 0.156/t = 2.316). Thus, *H2* is supported, as effort in both time and money commitments is connected with learning how to utilize technology. The result is also supported by previous studies, e.g., Rose et al. (2016).

As proposed in *H3*, social influence is positively associated with technology usage intention (β = 0.156/t = 2.316). Thus, *H3* is supported, as social environment that influences farm development can influence a farmer's future use of new technologies. The result is also supported by previous studies, e.g., Kuzcera (2006) and Foster and Rosenzweig (1995).

As proposed in *H4*, facilitating condition is positively associated with use behavior (β = 0.322/t = 5.123). It can be concluded that a farm's organizational and technological infrastructure would support the utilization of the system, thus confirming *H4*. These results are consistent with those of earlier investigations (see Popova and Zagulova, 2022).

As proposed in *H5*, government social power is positively associated with use behavior (β = 0.355/t = 5.674). It can be concluded that the government supports farmers' interests to give them information and services in the form of agricultural information systems, thus confirming *H5*. These findings are consistent with previous study results (see Stevens et al., 2005; Valentine, 2009).

As proposed in *H6-H8*, the path coefficients of performance expectancy, effort expectancy, and social influence moderated by farm size (-0.080, -0.075, and -0.070, respectively) are very low and was not significant.

As proposed in *H9*, intention to use technology is positively associated with use behavior (β = 0.224/t = 5.425). It can be concluded that the farmer's intention will have a substantial favorable impact on how people use technology, thus confirming *H9*. These findings are in line with the findings reported in past studies (see Venkatesh et al., 2003).

Table 4: Path coefficients.

Path	β	Error	Beta	t-value	p-value	*Supported?*	Q^2	f^2
PE → INT	0.259	0.180	0.063	3.960	0.000	Yes	0.099	0.054
EE → INT	0.156	0.246	0.074	2.316	0.021	Yes	0.099	0.019
SI → INT	0.138	0.166	0.064	2.062	0.040	Yes	0.099	0.019
FC → BEH	0.322	0.395	0.068	5.123	0.000	Yes	0.192	0.105
GSP → BEH	0.355	0.360	0.055	5.674	0.000	Yes	0.192	0.129
PE*FS → INT	-0.080	-0.121	0.087	1.218	0.224	No	0.099	-
EE*FS → INT	-0.075	-0.034	0.083	0.817	0.415	No	0.099	-
SI*FS → INT	-0.070	-0.067	0.053	1.678	0.094	No	0.099	-
INT → BEH	0.224	0.176	0.050	5.425	0.000	Yes	0.192	0.083

The term "effect size" (f^2) refers to the change in R^2 that occurs when a certain exogenous is eliminated from the construct (Selya et al., 2012). The model's effect sizes for both intention to use technology and use behavior were of a weak size. However, the Q^2 values of above 0, meaning that these variables have predictive abilities.

6. Conclusion

The results of the study reveal that the proposed theoretical model is carried out with context to farmers in Indonesia. Based on evidence from existing research, this study suggests that government social power can be used as an exogenous variable from the UTAUT model to support future research. In addition, this study found a relationship between variables that had not been found in the main UTAUT model. Some of the paths identified in this study is introducing a new variable, namely governance social power (GSP) on use behavior. This study did not use the main UTAUT model moderators (e.g., gender, age, experience), but farm size as the moderator.

The research findings indicate a number of practical implications. First, based on the evidence of current study, government support not only positively impacts behavior in using precision agricultural technology, but also has the highest impact among all predictors for use behavior. The findings indicate that the government should encourage and helps farmer to use e-commerce to assist extend output channels by developing pertinent policies and pooling financial resources, greatly allaying their concerns about adopting new technologies. The study results also show that social influence and favorable circumstances affect farmers' intentions to use technology. This suggests that a farmer's social network and favorable smart technology usage settings are crucial in fostering farmer innovation, a crucial predictor in precision agriculture. This suggests that social connection and supportive environments are essential in developing an atmosphere that will allow farmers to adopt technology.

The results of this study have a number of implications for research. First, this study extends prior research by showing that government social power can be considered an important variable to further understand of this issue addressed in UTAUT within the context of precision agriculture.

First, the findings indicate that there is a significant positive effect of facilitating conditions on use behavior and a significant positive influence of government social power on use behavior. Accordingly, we respond to a call by Popolova and Zagulova (2022) and Stevens (2005). Inconsistent with previous study results (e.g., Schukat and Heise, 2021), the results of the moderation test cannot be accepted because performance expectancy, effort expectancy, and social influence cannot be moderated by farm size on intention to use technology. The reason could be due to too small a sample size.

Because different demographic groups utilize the Internet differently, conducting an online survey may have limitations on its ability to be representative of the population. Future studies could analyze farmers in additional regions, as shown in Table 1. The type of farming the farmers conduct may also lead to groupings among the farmers. Investigating, for instance, the variations in commodities grown by rice and corn growers. This would make it possible to pinpoint the factors that determine behavioral intention in terms of farm operations even more precisely.

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