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Farmers' Intention as Mediator: Does Government Social Power Predict Real Use Behavior of Smart-Farming Technology?

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Abstract. Innovative technologies related to smart farming are expected to have a significant impact on the ability of agriculture to adapt to climate change and sustainable farming. The adoption of smart agricultural solutions by farmers, and in particular their application, is crucial for their success. Understanding the variables that influence farmers' decisions to employ these technologies is crucial in light of this. In order to close this knowledge gap, 301 farmers in West Sumatera, Indonesia, were questioned via an online survey in 2021. Results from structural equation modeling and multilevel regression analysis showed a positive and significant correlation between real farmer use behavior and government social power. Additionally, the results also show that the mediation effect of farmers' intention for government social power in resilience to the actual use behavior was significant. Our results deepen and go beyond previous research on government social power. 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. The important elements that will help farmers continue agriculture as well as becoming able to adapt to technology are identified in this research.

Keywords: government social power, intention to use technology, precision agriculture, use behavior.

1. Introduction

Food security, food safety, sustainable development, and health challenges have long plagued agriculture, particularly in developing nations like Indonesia (Wiliam et al., 2021). Prioritizing various supports for enhancing the performance and contribution of Indonesia's agriculture industry is still necessary, the corresponding sector still needs to receive a lot of attention (Rozaki, 2021). Agriculture development in general is one of the most important initiatives made by agricultural organizations to inform farmers in an effort to increase their production and well-being (Jhon & Babu, 2021). For those who require it or are facing socioeconomic difficulties, agricultural development is a type of informal education that provides direction through educational activities so that the farmers can increase their knowledge and skills (Zhara, 2018). The agricultural sector is Indonesia's main economic activity and a key driver of the nation's economic growth, as such, it deserves top attention in terms of planning the sector's development and incorporating the right innovations and technology (Utami et al., 2019).

The Indonesian government has also pushed and received support for the use of information and communication technologies in rural areas of the country (Amin, 2018). In terms of television, mobile phones, and radio, farmers have a significant amount of technology access and ownership at the country level, despite the fact that farmers' access to the internet was still somewhat limited (Ministry of Communication and Information Technology, 2015). It is likely still limited how new electronic media, like the internet, are used to promote the real economic operations of rural and farming communities (Hermawati, 2021). Even if information and communication technologies have the potential to be crucial for agricultural growth on a global scale, the reality is that only some farmers have access to electronic media (Lubis & Sulistiawati, 2020) Therefore, it would be crucial to conduct study on how farmers in Indonesia's rural areas access and use the technologies, as well as how the government power supports them.

In order to identify and describe the relationship of government social power toward the behavior of farmers to the agricultural information technology that supports their agricultural operations, research is required. The findings of this study can be applied as a plan for empowering farmers and enhancing access to information technology so that farmers can be connected and assisted maximally in meeting their requirements and discover methods that the government can assist farmers and agricultural empowerment. Furthermore, this research aims to investigate the relationship between government social power and the farmers' use behavior mediated by the farmers' intention to use the technology.

2. Literature Review

We begin by giving a succinct outline of the government social power in this section. We then introduce the background of precision agriculture and agricultural information system.

2.1. Government social power

According to the stakeholder influence theory, stakeholder salience is determined by a number of factors, including power (Frooman, 1999). Governments typically have significant control over businesses through taxation or regulation (Marquis & Qian, 2014). Utilizing social power entails influencing others by using resources, reprimands, and restrictions while taking into account their requirements and capacity to analyze their circumstances (Keltner et al., 2003). Influencing other people's actions in order to enforce compliance with one's authority is a key component of effectively using social power. In this regard, scholars have thought about how connections between supervisors and subordinates and how they may mold a subordinate's conduct may play a part in power imbalance (Gibson, 2019). For instance, depending on the type and extent of their supervisor's social authority, those who wish to use knowledge may seek it outside the company (Lee et al., 2019).

The current study model was developed using the features of expert power, referent power, legal power, coercive power, and reward power from Hinkin and Schriesheim's (Hinkin &Schriesheim, 1989) social power model. We argue that the five bases of social power have a variety of impacts on a person's affect based on the social power model. These five power bases can be converted into three different types of social power (French & Raven, 1959). Coercive power, reward power, and legitimate power are all described as having power through control, whereas legitimate power is defined as having power through authority. Expert power, referent power, and influence power are all examples of power through persuasion.

A pre-existing standard or norm that the power-expressing partner acknowledges serves as the foundation for legitimate authority (Hofmann et al., 2017). This viewpoint assumes that the spouse acknowledges the actor's right to support their position. A person in this situation has the legal right to command their spouse to do something, and the spouse will be required to comply. Most people believe that power is just and equitable. People feel compelled to sustain and defend the existing social institutions (Resnik & Elliott, 2016). They keep creating social hierarchies even when it is not necessary. People want to think that just authority is making decisions regarding their fate (Lee et al., 2019). This viewpoint significantly distorts how they perceive the actors' abilities (Stevens & Fiske, 2000). When they are associated with an authority figure, people are more likely to believe that it has virtues. Team members commonly engage in institutionalized mutuality. The institution has a responsibility to advance this confidence. As a result, individuals need to have more trust and confidence in a legal authority. Partners are happier when legitimate authority produces positive results since those results are perceived as being better.

We investigate the connection between government social power and the behavioral use of agricultural information systems since the government is a significant influencing factor (Hosman, 2010). We define government social power as the capacity of a government to affect farmers' behavior by applying the general definition of social power to a rural context. Since power is the asymmetrical control over one's own and another person's outcomes (Fiske, 2006), having social power gives one the chance to influence events to suit one's own interests and goals. On the other hand, having low social power makes it more likely that one's goals will be dependent on others (Sassenberg et al., 2012). Therefore, social power will also lead to "heightened responsibility for the outcomes of others who depend on the self," in addition to opportunities and self-interest (Zhong et al., 2006). Government influence over farmers' adoption of agricultural information systems is therefore implied by the government's social power over them.

2.2. Precision agriculture

Precision agriculture is an integrated and sustainable farming method that uses cutting-edge technology to increase farm profitability by reducing negative environmental consequences and labor expenses(Mokariya, 2020). Additionally, precision farming is anticipated to employ fewer inputs, reducing harmful external environmental factors in the use of technology (Ammann et al., 2022)]. Using Internet of Things (IoT) technologies, agriculture can be more exact. Real-time data from sensors and AI systems can be sent and received by precision agriculture (Shin et al., 2022).. Farmers can measure the air, soil, temperature, and other aspects of their property using precision agriculture. The questions given to the theoretical level differ greatly between individuals and companies (Li, 2020)

2.3. Agricultural information systems

A system in which agricultural information is generated, transformed, transferred, consolidated, received, and fed back in such a manner that these processes function synergistically to underpin knowledge utilization by agricultural producers is the definition of an agricultural information system (Roling, 1988). Farmers, researchers, and government decision-makers have been identified as consumers of agricultural information systems in earlier studies (Kizilaslan, 2006).

There has been a lot of scholarly interest in the adoption of agricultural information systems. Alvarez and Nuthall (Alvarez &Nuthall, 2006) contend that agricultural information systems should be tailored to the needs of farmers and that factors influencing acceptance of these systems include age, education, operational proficiency, and personality. According to Gang and Ping (Gang & Ping, (2012), factors like education level, age, and income have an impact on farmers' willingness to pay for agricultural knowledge. According to Mackrell et al. (2009), adoption of agricultural information technology in Australia is influenced by both technological and human factors.

They discover that information systems with high adoption levels are adaptable to farmers' shifting needs. Precision agriculture is the use of information technology to gather data, process information, and assist decisions for agricultural output (Bongiovanni & Lowenberg-Deboer, 2009). Based on theories of technological acceptance and innovation diffusion, Aubert et al. (Aubert et al., 2012) investigate the adoption of precision agriculture in Canada. Their findings emphasize the significance of information technology components and farming skills being compatible.

The adoption of farm management information systems in Romania is hampered, according to Moga et al. (2012). by factors like the decline in the number of legal farmers, the potential decline in investment, the lack of interest on the part of information system developers, and the lack of skills on the part of farm managers and farmers. According to Martin and Abbott Martin & Abbot, 2011), the key factor influencing the adoption of information technology in rural Uganda is the ability to effectively respond to economic opportunities or threats. Hosman. (2010) ,emphasizes that by offering an initial incentive, governments can encourage the adoption of information technology.

2.4. Behavioral intention and use behavior

The majority of theories at the individual level are behavioral models. Some significant derivative models had developed from the theory of reasoned action (TRA), a general model for behavior prediction (see Fig. 1). The first hypothesis to systematically demonstrate that an individual engaging in a specific action is impacted by both the subjective norm with regard to that behavior as well as his or her attitude toward that behavior was the TRA theory, developed by Ajzen and Fishbein in (1977). The term "subjective norm" describes the individual's perception of what other important people will think of him or her if they engage in that conduct. With the right research design, TRA quantifies the effects of attitude and subjective norm and accounts for a number of inconsistent behaviors found in social science research (Ajzen and Fishbein, 1991).

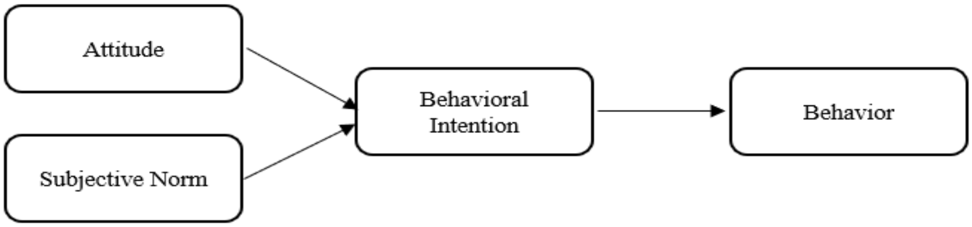

Fig. 1: Theory of reasoned action (TRA)

A more sophisticated general behavioral model derived from TRA is the theory of planned behavior (TPB). By adding a second element known as perceived behavioral control (PBC), Ajzen. (2002). improved the TRA and created the TPB model (see Fig. 2). PCB refers to a person's impression of how much control they believe they have over a particular activity. PBC has two components: whether the person believes they have the means to carry out the activity, and whether they believe there are opportunities to carry out the conduct (Ajzen, 2002). The direct relationship between PCB and actual behavior is one of its standout characteristics. Even if a person has the best of intentions, they may choose not to act on them if they believe there is no chance to do so.

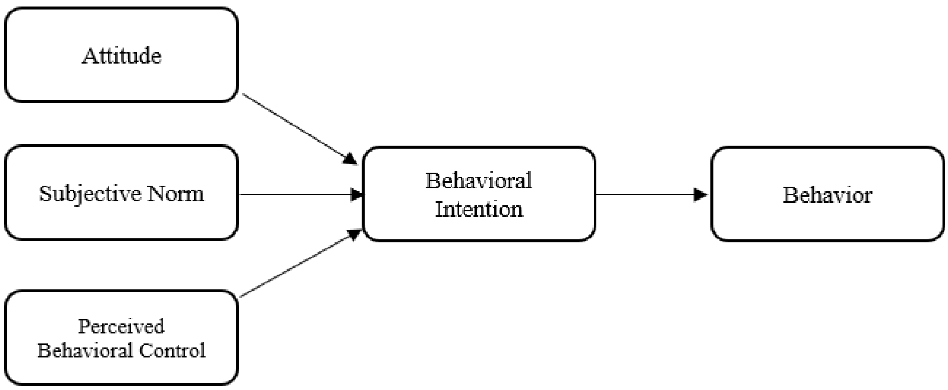

Fig. 2: Theory of planned behavior (TPB)

Technology acceptance model (TAM), which is, as its name implies, a specific model for predicting technology adoption, is another model created from TRA. Both TRA and TPB are general in nature and not intended for specific circumstances. These theories have been widely applied to comprehend how people behave in relation to, among others, the adoption of technology. Researchers must choose the proper variables for their study topics in order to apply these ideas. TAM, in contrast, uses two pre-determined constructs to predict adoption: perceived usefulness (PU) and perceived ease of use (PEOU). The model displayed is the original TAM, which was created after researching the use of word processing software (Davis, 1989). The creator had modified the model a few times in light of lessons learned from more applications (Davis, 1989). The only two constructs still used in these improvements for predicting adoption are PU and PEOU. Fig. 3 displays the TAM in its final form (Davis & Venkatesh, 1996).

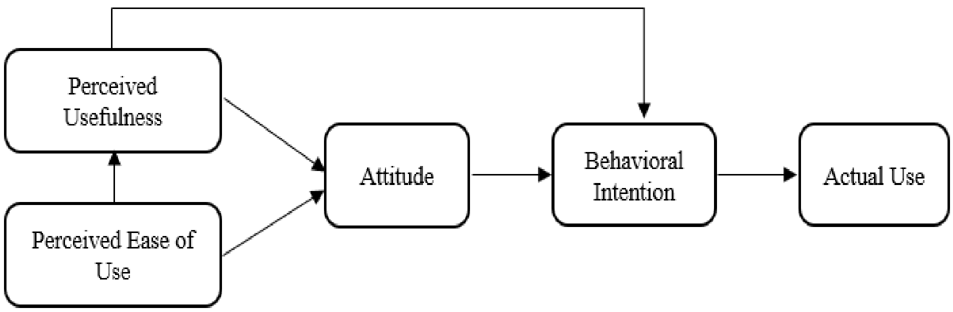

Fig. 3: Technology acceptance model (TAM)

Despite being the most widely utilized model for studying information technology adoption, TAM has undergone numerous iterations since its implementation. This is not surprising given that the model was developed through research on word-processing software adoption in office environments in the 1980s, which is relatively straightforward compared to challenges with later technology adoption. The suitability of the two structures, PU and PEOU, under various applications is another issue. According to earlier research, PU is still typically a reliable predictor of behavioral intention, but PEOU's relative importance and significance may be less clear (e.g., Gefen and Strau, 2000). As a result, the TAM model has been further improved by the Unified Theory of Acceptance and Use of Technology (see Fig. 4). In longitudinal field investigations of employee technology acceptance, the model explained around 70% of the variance in behavioral intention and 50% of the variance in actual usage by using more broad components and moderators to account for a larger range of applications. There are also some derivatives or improvements for each of these models. This study's primary model's relationship is shown in Fig. 4.

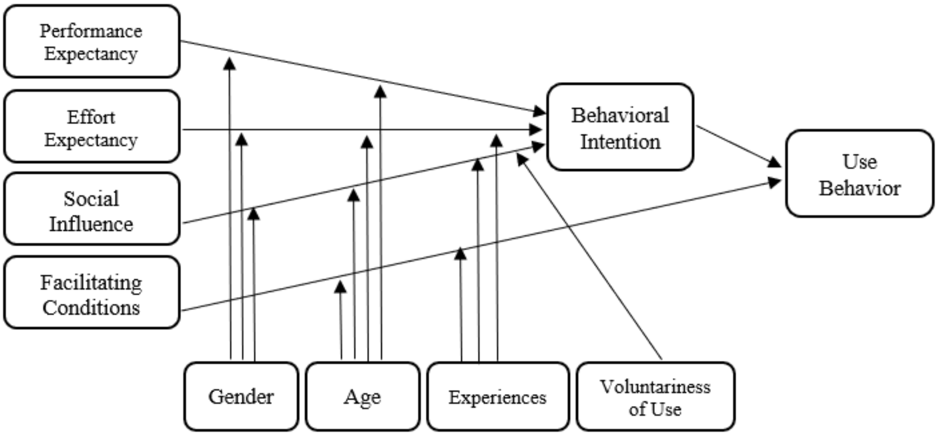

Fig. 4. Unified theory of acceptance and use of technology (UTAUT)

3. Hypothesis Development

The four main sources of government social power are coercive power, lawful authority, referent power, and expert power (Lu et al., 2014). Expert stakeholders are trusted, which strengthens their influence over farmers' usage intentions (Biong et al, 2010). Farmers follow the policymaker's advice when they think it is competent because they think it will lead to a better outcome. Government legitimate power is the conviction that a participant has the right to demand that other participants behave in a certain way (Michell et al., 1997). Because they believe they have a right to do so, farmers are forced to yield to government pressure. The basis for legitimate authority is this. The government's support for farmers' interests is indicated through referent power. The government funds agricultural information systems to provide services and information to farmers. If farmers believe the information is pertinent to their needs, it makes sense that they will believe the government is on their side. Therefore, from the perspective of social commerce, farmers will be receptive to the information system (Valentine, 2009). The government's capacity to reward farmers for adopting information systems is referred to as the government's reward power. Farmers who use information systems, in particular, gain more from official and private information services. Thus, the following hypotheses are formulated:

Hypothesis 1: Government social power and behavior intention to use technology are related.

Hypothesis 2: Government social power and usage behavior are related

Having or not having plans to use smart gadgets is a behavioral goal. With some moderator influence on the strength of the correlations between the independent variables and behavioral intention, it demonstrates farmers' perceptions of smart items. It is expected that behavioral intention will significantly positively influence how famers actually use smart products (Schukat and Heise, 2021). The conversation enables us to state the following claim:

Hypothesis 3: The farmers' intention to use technology has an impact on usage behavior.

3.1. 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.

3.2. 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.

4. Methodology

Cluster random sampling was the method of probability sampling employed in this investigation. One out of nine groups of farmers was randomly selected using cluster random sampling. To represent Indonesia, the population of farmers who utilize technology is drawn from West Sumatera, which has a total of 1,320 (54.95% of the whole country). The other eight groups were from West Java (15.40%), East Java (12.91%), Central Java (7.54%), North

Sumatera (3.29%), Yogyakarta (2.87%), Western part of Nusa Tenggara (1.58%), Riau (1.00%), and North Sulawesi (0.46%).

From the demographic profile (see **Table 1**), we can see that the gender split is almost 50-50, age group is about 26 to 45, completed education level is dominated by high school education at 48%, top commodities are corn and rice (37% and 34%, respectively), most years of being a farmer is from 6 to 10 years (26%), land area is less than 1 hectare, majority of land ownership status is mostly self-owned at 86%, and period of using the precision agriculture application is from 1 to 6 months. The sorts of farmers investigated are based on those who have harvested using precision agriculture technologies.

Table 1: Profile of the respondents.

No.	Profile	Characteristics	N	%
1	Gender	Male	145	48%
		Female	156	52%
2	Age	15-25	33	11%
		26-35	95	32%
		36-45	95	32%
		46-55	53	18%
		>55	25	8%
3	Education Level	Did not pass elementary	12	4%
		Elementary school	26	9%
		Middle school	61	20%
		High school	143	48%
		Higher education	59	20%
4	Commodity	Rice	103	34%
		Sweet potato	4	1%
		Corn	110	37%
		Chilli	12	4%
		Nuts	3	1%
		Combination	37	12%
		Other commodities	32	11%
5	Years of being a farmer	1- 5 years	94	31%
		6-10 years	79	26%
		11-15 years	45	15%
		16-20 years	29	10%
		>20 years	54	18%
6	Land area	<1 hectare	258	86%
		1-4 hectares	38	13%
		>4 hectares	5	2%
7	Land ownership status	Own land	165	55%

		Rent	45	15%
		Family owned	80	27%
		Lease	11	4%
8	Period of using precision agriculture app	<1 month	38	13%
		1-6 months	81	27%
		7-12 months	74	25%
		13-18 months	76	25%
		19-24 months	32	11%
9	Part of farmers' society/association?	Yes	271	90%
		No	31	10%

This survey was administered from June to September 2021, starting with planning, data collecting, processing, and analysis. The poll was distributed online to participants using an online survey platform that contained 4-Likert Scale items in an effort to increase response rates. The comments target primarily farmers who have been using the smart app as a communication tool. The questionnaire was made available online and the responses were gathered using Google Form and WhatsApp. The primary research data for the study are the questionnaire's results. The right responses for the research's criterion will be promptly provided by the questionnaire. The survey options range from (1) Strongly Disagree to (4) Strongly Agree on the actual questionnaire

5. Results and Discussion

The PLS-SEM approach, sometimes referred to as partial least squares structural equation modeling, is a two-step process that uses both evaluative measurements and structural models to analyze data. The composite reliability (CR), a score that gauges the latent variables of the concept, must first be tested. The CR must be 0.7 or greater to be considered suitable (Lin et al., 2020). All constructs' average variance extracted (AVE) scores exceeded the 0.5 cut-off, indicating good convergent validity (Hair et al., 2017).

When discussing measuring tools or instruments, validity relates to how well they can measure what has to be measured. The values in **Table 2** indicates that government social power, intention to use technology, and use behavior all have the average variance extracted (AVE) values of 0.577, 0.630, and 0.544, respectively. Since all variables are accurate and legitimate, the AVE values meet the minimum requirement of 0.5 (Hair et al., 2017).. Therefore, employee engagement, role benefit, and innovative behavior are fundamentally accurate and valid variables to employ in this study.

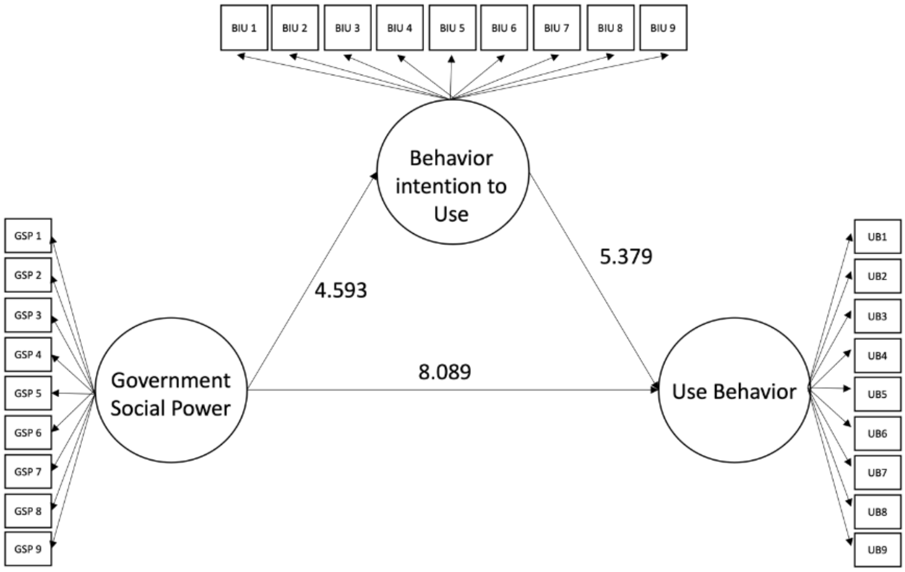

Fig. 5. Results of the PLS analysis

To calculate the route coefficients for the model, we used the PLS-SEM approach. Then, we conducted a second bootstrapping study with 5,000 subsamples and a 95% confidence level to determine the standard error and *p* value for each path coefficient.

Table 3. Correlations, means, and standard deviations.

Variable	Mean	*SD*	GSP	BU
GSP (Gov't Social Power)	3.32	0.55		
BU (Behavior Intention to Use)	3.11	0.41	0.48	
UB (User Behavior)	3.01	0.38	0.51	0.62

This study evaluated the influence of government social power on use behavior, and the mediating role of behavior intention to use technology in this relationship. Prior to analysis, the data were evaluated for normality and linearity and confirmed to be internally consistent (see Table 2). The residuals were then examined to ensure proper statistical analysis applications. The findings showed that the data for the constructs satisfied all necessary presumptions.

The means, standard deviations (SD), and Pearson's inter-correlations for each of the individual constructs used in this investigation are displayed in Table 3. Government social power (M = 3.32; SD = 0.55) and behavior intention to utilize technology (M = 3.11; SD = 0.41) were both indicated by the descriptive statistics. Several moderate relationships between the research variables were discovered. The findings revealed that user behavior and government social power had positive and moderate correlations (r=0.41; p<0.05), and that user behavior and behavior intention to use had positive and moderate connections (r=0.40; p<0.05). This implied that user behavior increased in proportion to the social power of the government.

Table 4. Path coefficients.

Path	*β*	Std. Error	Beta	*t*-value	*p*-value	*Decision*
GSP → BU	0.233	0.173	0.069	4.593	0.000	Reject H0
GSP → UB	0.355	0.360	0.055	8.089	0.000	Reject H0
BU → UB	0.224	0.176	0.050	5.379	0.000	Reject H0

Note: GSP: Gov't Social Power; BU: Behavior Intention to Use; UB: Use Behavior; Adjusted R^2=0.291

The model summary and coefficients for the user behavior model are shown in Table 4. To determine the elements influencing the farmers' use behavior, a path coefficient was computed. To prevent biased estimation, the adjusted R^2 value was utilized. In this study, the intention to use and government social power may account for 29.1% of the variance in user behavior, according to the coefficient of determination (Adjusted R^2=0.291). Table 4 demonstrates that H1, H2, and H3 were accepted. The biggest predictor of the farmers' usage behavior was government social power, according to coefficient values for all the hypotheses (see Figure 5): GSP to BU (β =0.233, p<0.05), GSP to UB (β =0.355, p<0.05), and BU to UB (β =0.224, p<0.05).

Further investigation reveals that BU mediated the interaction between GSP and UB. Table 4 demonstrates that the direct effect of GSP on BU (β = 0.233, SE = 0.173, t = 4.593, p<0.001) and the direct effect of BU on UB (β = 0.224, SE = 0.176, t = 5.379, p<0.001) were both statistically significant. According to the 5,000 bootstrap calculations, the farmers' intention to utilize technology had a mediation impact (i.e., an indirect effect) on the connection between government social power and use behavior (a x b = 0.233 x 0.224 = 0.052), indicating that this indirect effect was significant.

6. Conclusion

This study examined the influence of government social power on use behavior and the mediating role of behavior intention to use on the relationship between GSP and UB of West Sumatera farmers. The research findings of this study confirmed the significant influence of government social power on use behavior of farmers in West Sumatera, and the existence of the mediation effect of behavior intention to use technology. This evidence is supported by the data from the SEM which shows that government social power and behavior intention to use were significantly contributed to the explanation of the variance in use behavior. This result is aligned with prior research that suggests GSP influenced BU and UB (Biong et al., 2010, Schukak & Heise ., 2021).

It is pertinent to look into how smart products can be used and designed for farmers in order to ensure that farmers' use behavior is ensured not only in West Sumatera but on a national, even international, level because this study identified significant determinants of the farmers' behavioral intention and use behavior regarding smart products. Smart farming and smart products have the potential to help farmers produce in a way that is more climate- and resource-friendly, sustainable, and profitable.

To improve the environment for agricultural development operations, however, both the federal and local governments as well as the private sector are still required. A couple of perspectives—empowerment of human resources and information technology resources—are required as a strategy for empowering farmers in this era of information technology disruption. The best way to empower human resources is to maximize the role of young farmers. To empower information technology resources, increase the percentage of farmers who own smartphones through a credit program, and expand the number of smartphone applications for agricultural products, starting with upstream to downstream activities.

The ability of an online survey to be representative of the population may be constrained. Future research might examine farmers in different areas. Groupings among farmers may also result from the type of farming they do. Contrasting, for instance, the products produced by growers of sweet potatoes and chillies. In terms of farm operations, this would make it possible to identify the variables that determine behavioral intention even more precisely.

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