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The Role of the Theory of Planned Behavior and the Technology Acceptance Model in Determining the Adoption of Innovative Agricultural Technology by Small-Scale Farmers

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This research aims to examine the mediating effect of the two dimensions of the Technology Acceptance Model (TAM) (perceived usefulness (PU) and perceived ease of use (PEOU)) on the relationship between Theory of Planned Behavior (TPB) variables (attitude, subjective norms, and perceived behavioral control (PBC)) and small farmers' intention to adopt innovative technologies in agriculture in Malaysia. Data was collected using an online survey. The online survey link was sent to a total of 384 respondents via WhatsApp and emails; however, 289 responses were received back, and finally, only 270 responses were fit for analysis. The remaining 19 responses were rejected due to incomplete information. The collected data was analyzed using partial least squares structural equation modeling (PLS-SEM). The research found that both dimensions of the TAM partially mediated the relationships between the dimensions of TPB and small-scale farmers' intention to adopt technological innovation in agriculture. The results also showed that all of the predictive variables had positive and significant effects on small-scale farmers' intentions to embrace technology in agriculture, except for PEOU, which had a negative impact on intention. The results show Beta values of 0.356, 0.198, 0.412, 0.179, and -0.14 between attitude, PBC, subjective norms, PU, and PEOU, respectively, on small-scale farmers' intentions to use new technology in agriculture. Also, Beta values of 0.355 and 0.203 were found between attitude on PEOU and PU, respectively. PBC and PEOU demonstrated beta values of 0.383 and 0.411, respectively, on PU. Subjective Norms and PEOU demonstrated Beta values of 0.240 and 0.339, respectively, on PU. The R2 value shows that 86.8% of the small-scale farmers' intention is explained by the TBP and TAM. Also, the results showed that the predictors of perceived usefulness and PEOU are, respectively, 80.3% and 81.9%. This study may be applied only to small-scale farmers rather than the entire population of farmers in Malaysia. However, this was one of the few studies that explored small-scale farmers' intentions to adopt innovative agricultural technologies in Malaysia through the lens of the TPB and the TAM. This study viewed the importance of developing innovative agricultural technologies that can make a difference and should be user-friendly.

Keywords: Small-scale farmers, Theory of Planned Behavior, Technology Acceptance Model, Innovative Farming,

INTRODUCTION

During the past two decades, there has been a rapid increase and widespread technological innovations in agriculture, especially in developed countries. The use of technological innovations in agriculture has the potential to increase productivity and reduce costs while promoting environmental sustainability as well as improving the quality and quantity of agricultural produce (Hoque et al., 2017; Bessen, 2015; Junaydullaevich, 2020). However, the limited amounts of the world's arable lands are being taken away by rapid urbanization and climate change; natural resources, fresh water, and biodiversity are rapidly degrading (Elferink & Schierhorn, 2016; Schwab, 2018; Stacey McDaniel, 2019). Therefore, the need to improve efficiency and productivity in agriculture is becoming increasingly important. Thus, agricultural resources must be distributed more efficiently through the use of innovative technologies. Technological innovation in agriculture in Malaysia has made some progress through advances in information and communication technology, including the widespread availability of mobile phones and the Internet (Aisyah et al., 2012; Alam et al., 2021). However, many innovative agricultural techniques have not yet been utilized their full potential and are still in the demonstration stage in Malaysia (Gwadabe & Arumugam, 2021). Another contributing factor is the lack of research on farmers' adoption and use of technological innovations in agriculture, despite the economic importance of agriculture not only in Malaysia but in most countries of the world.

In order to reap the benefits of innovative technology, large commercial agricultural businesses invest a large number of resources and expertise in developing professional information technology. On the other hand, small-scale farmers lag in the adoption of agricultural information technology and therefore practice traditional and or mechanized farming, a situation that results in a setback and low profitability (Gwadabe & Amirah, 2017). This can lead to operational concerns and a loss of competitive advantage. Investing in technology is promising since consumers are increasingly looking for fresh and high-quality agricultural produce. Agricultural information technologies promise a higher quantity and quality of productivity and profitability (Fuglie et al., 2019).

Several theories, including the Diffusion of Innovation Theory, the Technology Acceptance Model (TAM), the Theory of Reasoned Action (TRA), and the Theory of Planned Behavior (TPB), have been established to explain the adoption of new technologies and users' behaviors (Taherdoost, 2018). The TAM and TPB have been used in this study as technological theories that link technology, behavior, intention, and acceptance of new technology. TPB refers to attitude as a "mental or neutral state of preparedness" that has been molded through experience that has a beneficial effect on an individual's reaction or behavior toward a phenomenon (Nalini, 2019; Ajzen, 2020). A person's attitude can influence how they perceive and respond to a given circumstance or object. According to previous research, a person's attitude towards technology is influenced by their willingness to use it (Ajzen & Fishbein, 2000). Subjective norms refer to the belief that an important person or group of people will approve and support a particular behavior (Ham et al., 2015). But according to research by Arumugam et al. (2017) and Adnan et al. (2018), mindset and perceived behavioral control (PBC) influence farmers' adoption of technology, whereas the subjective norm was not significant. Farmers' subjective norms about adopting technology may be irrelevant. PBC is an essential factor in understanding farmers' decisions to adopt new technology because of the human ability to manage their behavior. Based on prior studies, PBC has a moderate level of conversion to organic synthesis. On the other hand, people are more likely to adopt new technology if they believe it will give them greater control over their work (Walker et al., 2002; Herath, 2010).

In terms of TAM's criteria, perceived usefulness (PU) and perceived ease of use (PEOU) are the most important. PU is a term that refers to how customers view the experience's outcome (Wang et al., 2018). To encourage the use of technology, the power of PU is necessary (Wang et al., 2018). According to Adnan et al. (2017), there is a correlation between farmers' intentions to use advanced sustainable agriculture practices and their level of PU. TAM creates PEOU as an independent variable (Kurniasih et al., 2020). According to Muchran and Ahmar (2019), PEOU is the degree to which an innovation is easy to understand and use. According to the findings of the previous study, PEOU is a significant factor in determining whether or not an agricultural technology can be adopted (Caffaro et al., 2020; Flett et al., 2004; Gwadabe et al., 2021; Salimi et al., 2020). The TAM has received considerable attention in the literature. Psychological constructs PU and PEOU have a direct effect on the intention to adopt an information system, but PU exerts a more significant impact than PEOU (Caffaro et al., 2020; Kurniasih et al., 2020). The PU and PEOU moderate the effects of other external variables on the behavioral intention to adopt a technology (Caffaro et al., 2020). Problem detection in manufacturing and Web-based management systems are all examples of how the TAM has been utilized to explain individuals' intentions to accept technological breakthroughs (Kabir et al., 2021). As reported by Van et al. (2022), a small number of studies have used the TAM to forecast farmers' intentions to adopt technological innovations in the agricultural sector. These few studies have indicated a variety of patterns in the relationship between PU, PEOU, and farmers' intention to adopt, with PU and PEOU either being equally important in predicting farmers' intentions or with just PEOU reporting an impact. This research aims to examine the mediating effect of the two dimensions of the Technology Acceptance Model (TAM) (perceived usefulness (PU) and perceived ease of use (PEOU)) on the relationship between Theory of Planned Behavior (TPB) variables (attitude, subjective norms, and perceived behavioral control (PBC)) and small farmers' intention to adopt innovative technologies in agriculture in Malaysia. The results of this study are meant to help with the adoption of new technologies, strengthen Malaysia's plan for agricultural sustainability, and speed up the country's move toward greener productivity growth.

MATERIALS AND METHODS

Small-scale farmers in this study were defined as commercial producers of agricultural food commodities who cultivate agricultural land of not larger than two hectares. Small-scale farmers were chosen to be the study population because they are the backbone of Malaysia's agri-food economy. They represent more than 80% of all farmers in the country (Arumugam et al. 2017; Casey, 2016). However, Malaysian small-scale farmers lag behind in terms of adopting agriculture technology (Abdullah & Samah, 2013).

Given that the population of this study is 467,184 small-scale farmers (Department of Agriculture, 2018), the sample size determination table by Krejcie and Morgan (1970) suggested a sample size of 384 samples. Therefore, 384 small-scale farmers were selected via stratified random sampling technique from states with the largest number of small-scale farmers in Malaysia. These states are Johor, Kedah, Kelantan, Pahang, Perak, Selangor, Terengganu and Sabah. Out of 384 questionnaires distributed, only 289 answers were returned. In the end, 270 questionnaires were taken into account for the study. The remaining nineteen were excluded because the information provided was insufficient. This sample is thought to be suitable for evaluating the research model because the sample size to a parameter estimate ratio of 70% exceeds the lower bounds of normal distributions (Bentler & Chou, 1987), with all factor loadings greater than 0.70. In addition, the ratio of the sample size to the number of parameters to be estimated satisfies the requirements of a normal distribution (Guadagnoli & Velicer, 1988). An empirical examination of the research model proposed in this study was performed using partial least squares structural equation modeling (PLS-SEM), a statistical method that combines multiple regression and factor analysis to evaluate measurement tools and hypothesis testing. This method is useful in surveys using cross-sectional data (Bagozzi & Yi, 2012).

By testing the composite reliability values, reliability was assessed using the internal consistency process. As shown in Table 2, all variables showed reliability for the compounds (values greater than 0.7) (Hair et al., 2020). If the reliability of the indices (squaring of the external loads) is found to be less than 0.7, but the composite reliability and the AVE are suitable for measurement, the index are maintained as illustrated (Afthanorhan, 2013; Isah et al., 2021). Convergent validity was evaluated by calculating AVE values greater than 0.5 (Table 2), while discriminative validity was reviewed by the Fornell–Larker test (Table 3). The criterion for discriminant validity is that for each latent variable, the square root of the AVE must be greater than the correlation between the latent variables. The variables, as can be seen in Table 2, followed the criteria for discriminative validity. An HTMT value greater than 0.90, on average, suggested a potential problem with discriminative validity (Voorhees et al., 2016). All HTMT values in this sample were well below the 0.90 threshold level, indicating that discriminative validity was not a concern (see Table 2).

Since the PLS-SEM does not provide the overall quality of fit (GoF) indices, the value of R2 is widely used to assess the explanatory capacity of the model (Henseler et al., 2016). The fit of the model was evaluated using a diagnostic tool developed by Tenenhaus et al. (2005) known as the Goodness of Fit (GoF) index for PLS-SEM. The geometric mean value of the average variance extracted (AVE values) and average R2 values (for endogenous constructs) are used to determine the Goodness of Fit (GoF), which is calculated using the following equation: ($GoF = \sqrt{AVE \times R^2}$). While Tenenhaus et al. (2005) did not include any cut-off values for the aforementioned Goodness of Fit (GoF) index, Wetzels et al. (2009) provided the following cut-off values for evaluating the GoF study results: GoFmedium = 0.25; GoFlarge = 0.36; GoFsmall = 0.1; GoFmedium = 0.25; GoFlarge = 0.36. A good model fit, according to Henseler et al. (2016), indicates that a model is parsimonious and plausible. Tenenhaus et al. (2005) and Henseler et al. (2016) guidelines were used to calculate the Goodness of Fit (GoF) index for the model in this study, which is shown below.

RESULTS

A comprehensive review process was carried out as part of the data processing planning. Data were checked for outliers, missing values, demographic features, as well as data normality. There were a few missed values, so the commonly recommended method of mean substitution was used to manage them. This alternative is a SmartPLS built-in feature that substitutes missed data points with the average of all data points for the exact predictor (Farooq et al., 2018). One of the most sought-after advantages of the mean replacement strategy is that it does not change our sample size (unlike list-wise and pair-wise deletion) while maintaining the mean values of all variables (Clariana & Wallace, 2009). The Harman (1976) one-factor test is used in this analysis to see if there is any common method variance bias among variables. The researchers used Podsakoff et al. (2003)'s guidance and method to perform Harman's one-factor test. Both measurement scale objects were entered into a principal component analysis with varimax rotation so that any single factor indications could be detected from factor analysis. Based on the results presented in Table 1, it is concluded that this research does not suffer from the common method variance bias.

Based on a comprehensive examination of scaling models and structural models, it has been determined that all models (measurement and structural) are accurate. Moreover, these results show that the proposed theoretical model for the study has important predictive and explanatory ability. The results of the GoF calculation show a value of 0.769, which means that the combined output is good because the GoF value is greater than 0.36. The first step of Smart PLS Structural Equation Modeling is to describe a research framework or model-based schematic diagram based on theory. Also, the analysis was conducted using SmartPLS 3.2.9 graphics. The schematic diagram, which begins with the intent to adopt technology and TPB as well as TAM as mediating variables, is shown in Figure 1. Additionally, by the direction of the hypotheses proposed in the analysis, the arrows connecting the constructs of this study are identifiable. Single-headed arrows are used to check the causal effect of the sturdy construction. The summarized results of the SmartPLS Structured Equation Model are presented in Table 4 below.

The results of the respective construct of this analysis show the path coefficients, the standard deviation (STDEV), and the probability value (P-value). Furthermore, a significant positive correlation was detected between attitude and intention. The findings showed that a one percent rise in attitude would lead to a 0.356 increase in intention. In addition, the results revealed a significant positive effect of PBC on intention. The results indicated that a one percent increase in PBC would lead to a 0.198 percent increase in intention. Furthermore, a significantly positive relationship was revealed between subjective norms and intention. The findings showed that a one percent rise in subjective norms would lead to a 0.412 increase in intention. Also, a significant positive relationship was discovered between PU and intention. The findings showed that a one percent rise in PU would lead to a 0.179 increase in intention. In addition, the results revealed a significant negative effect of PEOU on intention.

The results indicated that a one percent increase in PEOU would lead to a 0.140 decrease in intention. Similarly, a significant positive relationship was discovered between attitude and PU. Furthermore, the findings showed that a one percent rise in attitude would lead to a 0.203 increase in PU. In addition, the results revealed a significant positive effect of PBC on PU. The results indicated that a one percent increase in PBC would lead to a 0.411 increase in PU. Also, a significant positive relationship was revealed between subjective norms and PU. The findings showed that a one percent rise in subjective norms would lead to a 0.339 increase in PU. Still, a significant positive relationship was discovered between attitude and PEOU. The findings showed that a one percent rise in attitude would lead to a 0.355 increase in PEOU. In addition, the results revealed a significant positive effect of perceived behavioral control on PEOU. The results indicated that a one percent increase in perceived behavioral control would lead to a 0.383 increase in PEOU. Furthermore, a significant positive relationship was revealed between subjective norms and PEOU. The findings showed that a one percent rise in subjective norms would lead to a 0.240 increase in PEOU.

In addition, the Variance Accounted For (VAF) value was then calculated by determining the size of the indirect effect in relation to the total effect (Hair et al., 2014). Thus, since the VAF was less than 80%, the mediating effect can be signified as partial mediation (Hair et al., 2014). The formula for computing VAF is as follows:

$$VAF = \frac{The\ Size\ of\ the\ Indirect\ Effect}{The\ Total\ Effect}$$

Mediating the effect of PU on the effect of Attitude on Intention

$$VAF = \frac{0.356}{0.356 + 0.203}$$

$$VAF = \frac{0.356}{0.559}$$

$$VAF = 0.637$$

$$VAF = 64\%$$

Mediating the effect of PEOU on the effect of Attitude on Intention

$$VAF = \frac{0.356}{0.356 + 0.355}$$

$$VAF = \frac{0.356}{0.711}$$

$$VAF = 0.501$$

$$VAF = 50\%$$

Mediating effect of PU on the effect of Perceived Behavioural Control on Intention

$$VAF = \frac{0.198}{0.198 + 0.411}$$

$$VAF = \frac{0.198}{0.609}$$

$$VAF = 0.325$$

$$VAF = 33\%$$

Mediating effect of PEOU on the effect of Perceived Behavioural Control on Intention

$$VAF = \frac{0.198}{0.198 + 0.383}$$

$$VAF = \frac{0.198}{0.581}$$

$$VAF = 0.341$$

$$VAF = 34\%$$

Mediating the effect of PU on the effect of Subjective Norms on Intention

$$VAF = \frac{0.412}{0.412 + 0.339}$$

$$VAF = \frac{0.412}{0.751}$$

$$VAF = 0.549$$

$$VAF = 55\%$$

Mediating effect of PEOU on the effect of Subjective Norms on Intention

$$VAF = \frac{0.412}{0.412 + 0.240}$$

$$VAF = \frac{0.412}{0.652}$$

$$VAF = 0.632$$

$$VAF = 63\%$$

The R^2 value shows the degree to which the variance-independent variables are explained by the independent variables. The R^2 estimates are shown in the model in Table 5. The result reports that 86.8 percent of its variance is explained by the TBP and TAM predictors. In other words, roughly 13.2 percent of the difference in intention itself is the error variance of intention. Additionally, the results of Table 5 estimated that the predictors of Perceive usefulness and PEOU are 80.3% and 81.9%, respectively. Similarly, in the present study, the predictive relevance Q^2 of all the exogenous latent constructs is small. According to Hair et al. (2014), as a relative measure of predictive relevance, the values of 0.02,0.15 and 0.35 indicated that an exogenous construct has a large predictive relevance for a certain endogenous construct.

Table 1: The Assessment for CMV in Dataset – Harman's One Factor Solution

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**24.752**	**42.677**	**42.677**	**24.752**	**42.677**	**42.677**
2	4.053	6.989	49.665	4.053	6.989	49.665
3	2.951	5.089	54.754	2.951	5.089	54.754
4	2.720	4.689	59.443	2.720	4.689	59.443
5	1.609	2.774	62.217	1.609	2.774	62.217
6	1.398	2.410	64.626	1.398	2.410	64.626

Table 2: Measurement Model

	Items	Factor Loading	Cronbach Alpha	CR	AVE
Intention			**0.906**	**0.928**	**0.682**
	I1	0.773			
	I2	0.785			
	I3	0.839			
	I4	0.879			
	I5	0.865			
	I6	0.807			
Attitude			**0.822**	**0.874**	**0.581**
	A1	0.769			
	A2	0.733			
	A3	0.793			
	A4	0.764			
	A5	0.751			
PU			**0.892**	**0.919**	**0.655**
	PU1	0.854			
	PU2	0.857			
	PU3	0.840			
	PU4	0.882			
	PU5	0.631			
	PU6	0.765			
PEOU			**0.911**	**0.927**	**0.588**
	PE1	0.815			

	PE2	0.821			
	PE3	0.810			
	PE4	0.819			
	PE5	0.738			
	PE6	0.798			
	PE7	0.708			
	PE8	0.771			
	PE9	0.790			
Perceived Behavioural Control			**0.814**	**0.876**	**0.640**
	PBC1	0.775			
	PBC2	0.777			
	PBC3	0.807			
	PBC4	0.839			
Subjective Norms			**0.775**	**0.855**	**0.598**
	SN1	0.654			
	SN2	0.829			
	SN3	0.840			
	SN4	0.756			

Table 3: Discriminants Validity

	Attitude	Intention	PBC	PEOU	PU	Subjective Norms
Attitude	**0.762**					
Intention	0.627	**0.826**				
PBC	0.612	0.761	**0.800**			
PEOU	0.608	0.627	0.554	**0.767**		
PU	0.621	0.649	0.565	0.590	**0.809**	
Subjective Norms	0.652	0.694	0.712	0.756	0.767	**0.773**

Table 4: Hetromonotrtait

	Attitude	Intention	PBC	PEOU	PU	Subjective Norms
Attitude						
Intention	0.729					
PBC	0.743	0.770				
PEOU	0.731	0.705	0.786			
PU	0.753	0.730	0.702	0.782		
Subjective Norms	0.626	0.734	0.706	0.714	0.725	

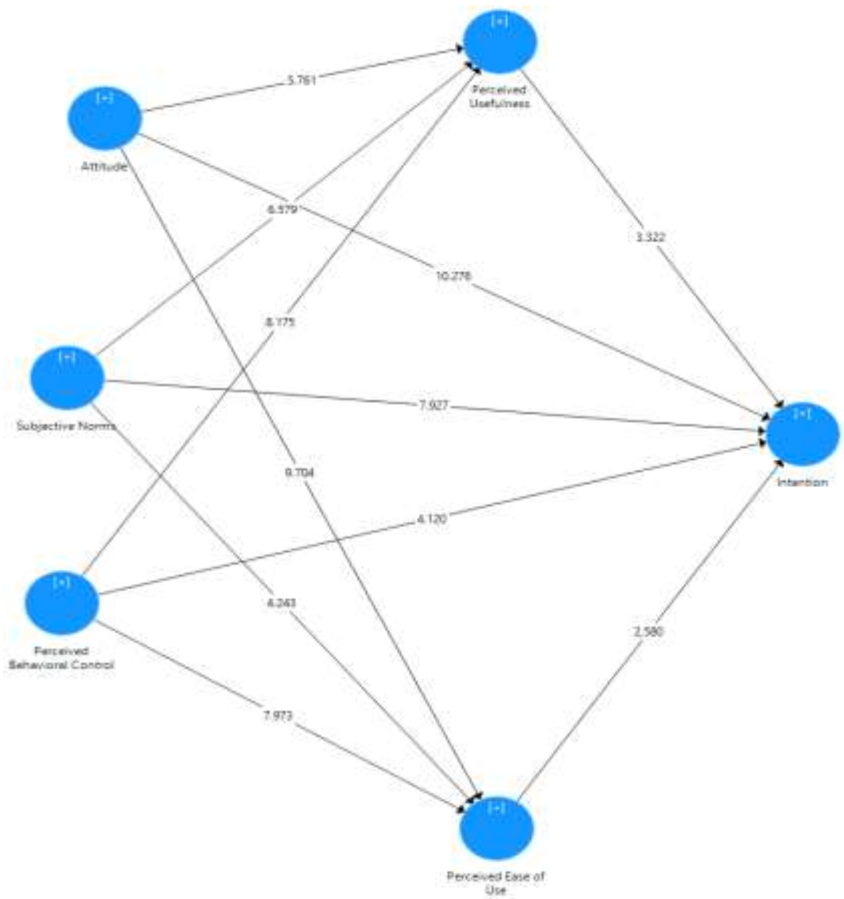

Figure 1: Path Coefficient

Table 5: Summary of Path Coefficients

	Beta	T Statistics	P Values
Attitude -> Intention	0.356	10.276	0.000
PBC -> Intention	0.198	4.12	0.000
Subjective Norms -> Intention	0.412	7.927	0.000
PU -> Intention	0.179	3.322	0.001
PEOU -> Intention	-0.14	2.58	0.010
Attitude -> PEOU	0.355	9.704	0.000
Attitude -> PU	0.203	5.761	0.000
PBC -> PEOU	0.383	7.973	0.000
PBC -> PU	0.411	8.175	0.000
Subjective Norms -> PEOU	0.240	4.243	0.000
Subjective Norms -> PU	0.339	6.579	0.000

Table 5 Summary of Goodness of Fit

	R^2	Q^2
Intention	0.868	0.550
PEOU	0.819	0.450
PU	0.803	0.482

DISCUSSION

Innovative technology is becoming increasingly prevalent in all areas, including agriculture. Small-scale farmers, particularly in Malaysia, are hesitant to adopt technological innovations for a variety of reasons, including the cost, technicality, and complexity of the innovations. This research aimed to determine how the two dimensions of the TAM (PU and PEOU) influence the relationship between the variables of the TPB (attitude, subjective norms, and PBC) and the intention of small-scale farmers in Malaysia to adopt technology in agriculture. This study, therefore, created a model by combining the TPB and the TAM. The results showed that the model has a good chance of predicting whether or not small-scale farmers in Malaysia would adopt innovative technologies in farming.

The direct relationships between the independent variables (attitude, subjective norms, and PBC) and small-scale farmers' intention to adopt technological innovations are all positive and significant. So, the results are consistent with earlier studies (Aboelmaged & Gebba, 2013; Mohr, & Kühl, 2021). Next, the relationship between PU and small-scale farmers' intention to adopt technological innovation was also found to be positive and significant, and the result is in line with earlier studies (Zeweld et al., 2017; Caffaro et al., 2020). However, the relationship between PEOU and small-scale farmers' intention to adopt technological innovation was found to be negative but significant and consistent with previous studies (Hua et al., 2019; Li et al., 2021). Attitude, subjective norms, and PBC have shown positive and significant influence in measuring small-scale farmers' PEOU of technological innovations in agriculture. The results are in line with Kurosh et al. (2010) and Zeweld et al. (2017). Moving further, attitude, subjective norms, and PBC have shown a positive and significant influence in influencing small-scale farmers' PU of agricultural innovations, and the results are consistent with previous studies (Borges et al., 2014; Zeweld et al., 2017). Lastly, the research found that both dimensions of the TAM partially mediated the effects of the TPB constructs on the farmers' plans to adopt new technology. These results show that the research model is effective at predicting farmers' intentions to adopt technological innovations in agriculture.

This study contributes to the technology adoption theories by fusing the TPB and the TAM in the context of small-scale farmers' adoption of innovative technologies in agriculture. The research model has tested the direct and indirect influences of the determinants of the TPB on small-scale farmers' intention to adopt innovative technologies. The study also tested the mediating roles of PU and PEOU in the relationships between the determinants of the TPB and farmers' intention to adopt technological innovations in agriculture.

The research model explains substantial variance, and the findings of the study confirmed the validity of the research model in measuring small-scale farmers' intention to adopt innovative technologies. Another theoretical contribution of this study is examining the mediating role of PU and PEOU within the relationship of attitude, subjective norms, and PBC on the one hand and farmers' intention to adopt technologies on the other hand. Combining the TPB and the TAM help will improve both theories and agriculture, especially small-scale agriculture.

This study would help policymakers, farmers, and non-government organizations develop innovative agricultural technologies that are affordable and user-friendly. The present study determined that attitude, subjective norms, and PBC, directly and indirectly, influenced small-scale farmers' intention to adopt innovative technologies in agriculture. The three constructs influence farmers' intentions indirectly through the mediation effect of PU and PEOU. Therefore, a change in small-scale farmers' attitudes, subjective norms, and PBC would influence their perceptions and, subsequently, their intention to adopt innovative technologies. Before introducing them to small-scale farmers, stakeholders should think about the usefulness and user-friendliness of innovative agricultural technologies.

CONCLUSION

Innovative technology has gained the attention of academicians and policymakers due to the role it plays in the sustainability of agriculture and food security (Gwadabe et al., 2021). Despite the recent surge in technology adoption studies, the role of innovative technology, especially on small-scale farms, is less studied. Thus, the current study investigates factors influencing farmers' behavioral intention toward adopting innovative technology among small-scale farmers. The research model of this study incorporates the TPB and the TAM to examine farmers' behavior with the intention of adopting agricultural information technology. For data analysis, Partial least squares structural equation modeling approach was used. Using stratified random sampling technique, 384 online survey links were sent to different farmers, 289 responses were retrieved after a thorough follow-up and 270 online questionnaires were found fit for data analysis. The results of the SEM revealed that all together, attitude, subjective norms, PBC, PU, and PEOU explained 86.8% of the variance in determining farmers' behavior towards the intention to adopt innovative technologies in agriculture. Regarding the mediating construct, PU was predicted by attitude, subjective norms, and PBC, which explained 80.3% of the variance. On the other hand, PEOU was also predicted by attitude, subjective norms, and PBC, which explained 81.9% of the variance. In addition to that, the predictive relevance of the research model was also found to be essential in measuring the respondents' intention to adopt technology in agriculture. The results also showed that all of the exogenous variables had positive and significant effects on intention, except for PEOU, which had a negative effect on intention.

Therefore, this study viewed the importance of assessing the role of the theory of planned behavior and the technology acceptance model in determining the adoption of innovative agricultural technology by small-scale farmers in Malaysia. In addition, the parties concerned should convince the target farmers about the relevance of the farming technologies. Focusing on training, orientation, and getting the younger generation in the farmers' homes involved in agriculture would be a key part of changing the farmers' thoughts and actions about using innovative technologies.

Like any other research, this study has some limitations that must be acknowledged for future research directions. First, this study was conducted among small-scale farmers. Therefore, future studies may include estate farmers as well in order to identify the gap between the two categories of farmers. As the literature shows, technology adoption rates are significantly higher among estate farmers.

Considering future research, this study is cross-sectional in nature. It is therefore suggested that future researchers investigate the phenomenon in a longitudinal study. Considering the COVID-19 pandemic resulted in many restrictions, including a shortage of labor and changes in market demands, and the current research was conducted during the pandemic, it is expected that results may differ in normal situations. Future researchers may replicate the survey in a post-pandemic context to get another perspective on the situation. Even though all the variances that determine the exogenous constructs are relatively high, other contributing factors may play important roles in determining farmers' intention to adopt innovative technologies. Therefore, future studies may expand or modify the current model to explore the phenomenon. Also, future studies may include the perspective of extension services and technology transfer diffusion roles of government and other and non-governmental agencies in Malaysia in order to have deeper look into the phenomenon. Finally, this study was conducted in Malaysia, so replicating it in southeast Asia and other parts of the world, especially other developing countries, could reveal interesting findings.

CONFLICT OF INTEREST

The authors declared that the present study was performed in the absence of any conflict of interest.

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AUTHOR CONTRIBUTIONS

UMG wrote the manuscript and analyzed the data. NA designed and collected the data. NAA reviewed the manuscript. IS proofread and edited the manuscript. All authors read and approved the final version.

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