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The acceptance of decision support system (DSS) in vegetable cultivation among farmers in Malaysia

[Penerimaan sistem sokongan keputusan (DSS) dalam penanaman sayuran di kalangan petani di Malaysia]

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Keywords: Vegetables farmers, acceptance, decision support system (DSS), technology acceptance model (TAM), structural equation modelling (SEM)

Abstract

In Malaysia, the agricultural revolution is vast and in line with technology advancement to maximise productivity whilst minimising use of resources. Current technology like the decision support system (DSS) improves crop quality, lowers cost and provide real time crop monitoring. Theoretically, DSS is a system based on artificial intelligence (AI) and Internet of Things (IoT) technology. With regards to the production aspects of mechanisation and agricultural inputs beginning with the preparation of soil, seeds, planting, plant care and harvesting, this system offers consultancy, technical assistance and professional advisory services. Currently, limited discussion is in place on the applicability and usage of these technologies in relation to Malaysian farmers' perception and acceptance of this technology. Therefore, the aim of this study is to identify the most dominant factor that influences DSS adoption in vegetable cultivation in Malaysia. This study has adopted the theory of Technology Acceptance Model (TAM) as its theoretical framework and the Structural Equation Modelling (SEM) was used to analyse factors affecting the adoption and acceptance of DSS among farmers. A total of 133 Malaysian vegetable farmers participated in this study. A self-administered questionnaire was used in a quantitative research strategy to acquire the sample. According to the study's findings, farmers' intentions to use a DSS for vegetable cultivation are significantly influenced by perceived ease of use, attitude and technological influence. This study has produced insightful data on different perceptions of farmers and is used as a springboard for creating a framework for analysing support systems that may better address the needs of farmers.

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Introduction

More than 1.8 million people are employed in Malaysia's agricultural industry, which continues to be one of the country's key economic sectors (Ministry of Human Resources Malaysia 2022). Agriculture is regarded as one of the most important components under the National Key Economic Areas (NKEA), due to its potential to accelerate economic growth by creating more jobs and increasing income for farmers. The implementation of 12th Malaysian Plan in Agriculture focuses on food security, modernisation and transformation of the agricultural sector, transfer of technology and enhancing capacity building (DOA 2021). However, there are challenges identified in vegetable cultivation that may slow down the sector such as small-scale production, limited technology application, declining number of arable land, environmental deterioration due to climate change, rapid urbanisation, ageing farmers and increased cost of production. Therefore, the adoption of industrial revolution 4.0 (IR 4.0) technology into agriculture could reduce the cost of input, increase the value of the products and sustain a healthy environment (Dung and Hiep 2017). Furthermore, in order to improve the competitiveness of the agricultural sector, farmers are encouraged to fully utilise modern technologies in their farms (Mat Lazim et al. 2020). In this perspective, the adoption of IR 4.0 in the agricultural sector could provide numerous benefits, particularly in terms of lowering production costs and enhancing product quality through effective farm management.

Farmers and scientists in agriculture face a significant problem in successfully managing information to enhance economic and crop productivity. The ability to accurately measure crop growth, as well as a scientific decision-making process to provide appropriate strategies based on truth, is crucial in making good decisions. To solve this issue, the data flow between decision processes and user input must be analysed and modelled for an efficient output and conclusion. Interactive computer programs assist decision-makers in developing alternatives, analysing their consequences, inferring and selecting appropriate options for execution. This contributes to the development of decision support systems that make agricultural science more accessible to farmers and scientists. This can be accomplished in part by utilising decision support systems (DSS), which provide precise and extensive information on agriculture for crop selection (Venkatalakshmi and Devi 2014).

Theoretically, DSS is a system based on Artificial Intelligence (AI) and Internet of Things (IoT) technology. Several studies have looked into the use of AI and IoT technology in agriculture, particularly in Malaysia. Both Qiang (2010) and Ferehan (2022) emphasise the potential of these technologies to increase data accuracy, reduce labour and improve farming decision making. Shahzadi (2016) and Devi (2020) emphasise the need of real-time data collection and proactive steps in reducing losses due to pest and disease. These studies highlight the revolutionary potential of AI and IoT in the agriculture sector, notably in Malaysia. However, there is currently limited discussion in the context of Malaysia on the applicability, usage and farmers' acceptance of these technologies for farming activities. With regard to the production including aspects of mechanisation and agricultural inputs beginning with the preparation of the soil, seeds, planting, plant care, and harvesting, this system will offer consultancy services, technical assistance, and professional advisory services. Thus, the aim of this study is to identify the most dominant factor that influences DSS acceptance in vegetable cultivation in Malaysia. This study hopes to help government agencies discover the farmers' perceptions and could also initiate programs to expand the importance of technology among farmers. Consequently, training the farmers, educating them appropriately and reorienting them to take up new activities through the adaptation of new technologies is of utmost importance.

Literature review

Internet of Things and Decision Support System (DSS) application

The Internet of Things (IoT) is a network of physical items or "things" that are outfitted with sensors, software and networking technologies to collect and share data with other systems and devices over the internet (Chander and Kumaravelan 2020). IoT has been progressively incorporated into farming, giving rise to a practice that is frequently referred to as "precision agriculture" or "smart farming." These networked devices are ubiquitous, from everyday objects such as an automated fertigation system, as well as a crop and pest management system**.** The application of IoT technology in agriculture leverages the potential to enhance farming practices, boost farm production, decrease food waste, improve crop quality and make farming more sustainable and profitable (Phasinam et al. 2022).

A decision support system or DSS, is a computer based information system that offers pertinent information and analytical tools to help farmers or organisations make well informed decisions (Zhai et al. 2020). DSSs are used in agricultural sector to support decision-making procedures that may contain intricate, ambiguous or semi-structured issues. In some circumstances, DSSs may include decision automation capabilities, allowing for the automatic determination of some routine or standardised decisions by specified rules and criteria. Weather forecasting and crop predictive analytics system for example is a comprehensive tool that combines meteorological data with agricultural data to provide insights and predictions related to crop yield, pest and disease management, and overall farm management (Hachimi CE et al. 2023). This system helps farmers, agronomists and agricultural organisations optimise farming techniques, increase crop yield and lower risks linked to weather related events**.**

Technology acceptance model (TAM)

The agricultural sector shows an increasing trend in line with the development of advanced technology, but farmers' acceptance on the adoption of technology in agriculture is still low (Suprehatin 2021), especially among smallholder farmers in this region (Suprehatin 2019). Besides the comfort of using conventional methods, the high cost of technology has become a constraint on the use of technology. Only farmers with large production capacities can use technology in agriculture. One of the factors of technology adoption is saving time and manpower. Technology adoption in the agricultural industry assists the applicant to do work easier hence it helps save time and manpower (Bonabana-Wabbi 2002). Accordingly, the technology acceptance model (TAM) analysis was employed in this study to examine farmers' level of acceptance on MARDI's DSS technology.

TAM was originally proposed by Davis in 1986 and has proven to be a theoretical model in helping to explain and predict user behavior of information technology (Legris et al. 2003). The adoption of new technology was measured with two primary factors influencing an individual's intention which are perceived ease of use and perceived usefulness. According to Verma and Sinha (2018), the variables used are reliable and valid constructs in predicting behavioural intention to use. Usefulness and ease of use have been shown to be the important drivers of technology adoption and prior perceptions influence the attitudinal aspect of behavioural decisions (Folorunso and Ogunseye 2008; Kutter et al. 2011; Pierpaoli et al. 2013). TAM is widely used to evaluate adoption in information technology and this is in line with the research conducted by Paul et al. 2003. However, Flett et al. 2004 was the first paper to apply a TAM in agriculture and highlighted the importance of socio-psychological factors as important drivers of technology acceptance and adoption and until now more studies related to farmers' behavioral towards technology have been evaluated using TAM such as the acceptance of genetically modified seeds (Voss et al. 2009), sustainable cultivation methods (Dessart et al. 2019), transport packaging (Kamrath et al. 2018), predict the use of natural pest control in rice production (Sharifzadeh et al. 2017) and the use of integrated pest management in horticulture (Rezaei et al. 2020). A study conducted by Mohr and Kuhl (2021) found that technology for agriculture that is still in the early stage of development needs to focus on acceptance instead of adoption and thus relies on the TAM.

Furthermore, the TAM is a very parsimonious model that allows researchers to include additional predictors associated with a particular behaviour (Lee 2016). Several scholars are suggested additional constructs that might be used to further improve its predictive validity. Originally, TAM included factors such as perceived ease of use (PEU), perceived usefulness (PU) and attitude (ATT). Unlike prior TAM literature, this research highlights the integration of perceived barrier (PB), social influences (SI) and technology influences (TI) into the original TAM model to investigate the relationship between farmers' behavioral intentions (BI) to accept the DSS technology in vegetable cultivation. The variables used in the research questionnaire are elaborated in *Table 1*.

Methodology

Sampling technique and data collection

This research involves quantitative methods, and the primary data were collected through a structured face to face interview with n = 133 farmers which was conducted between September 2021 – September 2022. Respondents were sampled using purposive sampling method from the list of vegetable farmers gathered by Department of agriculture (DOA). Descriptive and inference quantitative analysis were performed using statistical package for social science (SPSS) Version 23 and SmartPLS. Measures in the survey included in TAM are displayed in *Figure 1*. All measures included replication of indicators previously used in empirical research. A 5-point response scale (1 = strongly disagree to 5 = strongly agree) was used in the questionnaire.

Descriptive statistics

The descriptive analysis method was performed for initial analysis and to understand the data and determine the demographic profile of the respondents. In this study, the use of simple descriptive analysis enables to display of the status of IoT usage among the respondents.

Partial least squares: Structural equation modelling

The study used SmartPLS 3.3 software and partial least squares (PLS) analysis (Ringle et al. 2015) to analyse the research model, which included both the measurement model (reliability and validity) and the structural model (hypotheses) (Anderson and Gerbing, 1988)we provide guidance for substantive researchers on the use of structural equation modeling in practice for theory testing and development. We present a comprehensive, two-step modeling approach that employs a series of nested models and sequential chi-square difference tests. We discuss the comparative advantages of this approach over a one-step approach. Considerations in specification, assessment of fit, and respecification of measurement models using confirmatory factor analysis are reviewed. As background to the two-step approach, the distinction between exploratory and confirmatory analysis, the distinction between complementary approaches for theory testing versus predictive application,

Table 1. Summary of studies that used variables applied in this research

Variable	Findings	Author
Perceived ease of use (PEU) and perceived usefulness (PU)	This paper empirically analyses the influencing factors of farmers' willingness to use agricultural socialised service platforms based on micro survey data of 253 farmers in Heyang County and Dali County, Shaanxi Province, based on the technology acceptance model (TAM) that include perceived ease of use and perceived usefulness as well as risk preference theory.	Zhang et al. (2022)
Attitude (ATT)	It was discovered that attitude has the biggest impact on the intention to use technology. This suggests that the intention to utilise technology is significantly influenced by one's attitude towards new technology, particularly technology that is not yet generally available. The usefulness and intention are related through the attitude mediator.	Mahattanakhun and Suvittawat (2023)
Perceived barrier (PB)	Effective strategies should be created to foster farmers' positive attitudes, awareness of societal norms, perceptions of their talents, and reduction of perceived dangers in order to boost their enthusiasm for implementing the technology.	Li et al. (2020)
Social influences (SI)	The theory of planned behaviour (TPB) first presented the concept of social influence (SI) as a significant social factor for examining the uptake of computer-based technology.	Faqih (2019)
	The adoption of technology has also been strongly impacted by social influence.	Sulistyaningrum et al. (2023)
	Research has shown that social effects have a substantial impact on human behaviour in general and technology adoption.	Ilham and Ekaningtyas (2020)
Technology influences (TI)	This study on smallholder farmers in Mexico discovered that the intention to adopt agricultural apps is predicted by how farmers evaluate the technological infrastructure and gain new knowledge through the use of an app. The study's findings are helpful for practitioners and app developers designing digital decision support tools.	Molina-Maturano et al. (2020)
	Farmers' readiness to adopt new technologies is significantly influenced by the sort of technology promoter and how valuable they view the technology to be.	Qi et al. (2021)

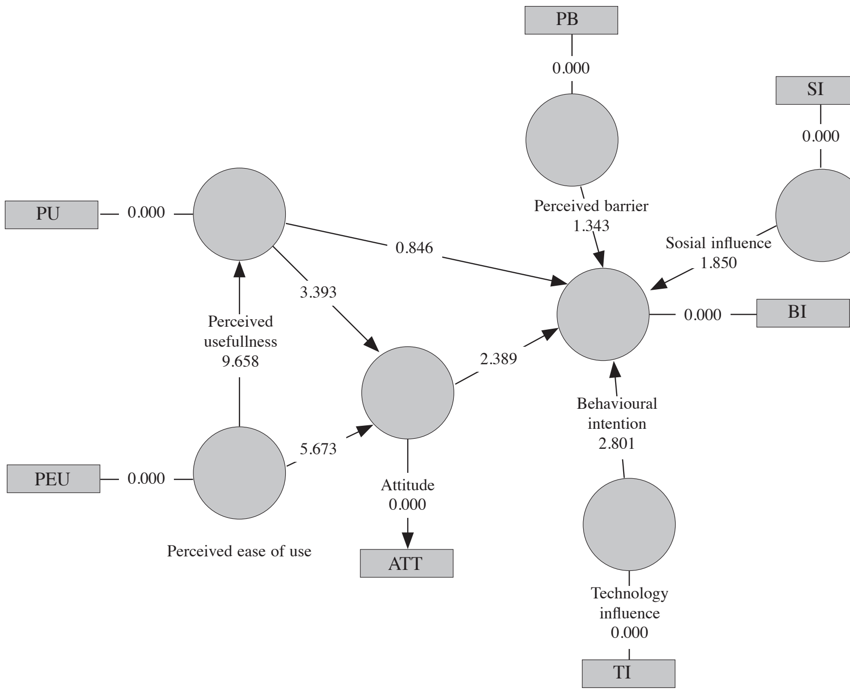

Figure 1. Structural model

and some developments in estimation methods also are discussed. (PsycINFO Database Record (c. Before the SEM is used, some criteria must be fulfilled such as common method variance and normality.

The data used in this study were collected through a survey which have a single source bias issue that may need to be addressed. The Common method variance (CMV) might have been an issue because both independent and dependent variables were collected simultaneously from the same respondents (Avolio et al. 1991). Podsakoff et al. (2003) recommends and adopted a single common method factor approach to control CMV. The PLS marker variable approach was used to create a method factor (Ronkko and Ylitalo 2011) that were collected in the same survey but are not included in the model being tested: (1) “Once I’ve come to a conclusion, I’m not likely to change my mind;” (2) “I don’t change my mind easily;” and (3) “My views are very consistent over time (Oreg 2003).” Second, a method factor was created using the marker indicators as an exogenous variable predicting each endogenous construct in the model. The method factor model and the baseline model were then compared, and the results showed that the significant pathways from the baseline model were still significant in the method factor model. Thus, based on Lin et al. (2015), we can say that there was no CMV issue with the data. Additionally, Harman’s single factor test was also applied to assess the presence of CMV (Podsakoff et al. 2003). The results showed that CMV was not a significant threat to the study as the value obtained was below 50%. Furthermore, an unrotated factor analysis of all items resulted in four factors with eigenvalues greater than one and the first unrotated factor accounted for 33.269%, indicating that the presence of CMV was not a concern in this study.

Then, the normality of the data was assessed using multivariate skewness and kurtosis analysis, as recommended by Hair et at. (2017) which is available at: bit.ly/farmersIOTacceptance. The results indicated that the Mardia’s multivariate skewness

(β = 10.64, p <0.01) was above the recommended cut of +1 and the Mardia's multivariate kurtosis (β = 74.41, p <0.01) was above the recommended cut of +20. These results suggest that the data collected was not multivariate normal. Therefore, the use of PLS-SEM in this analysis is appropriate.

Results and discussion

Demographic profile

The respondent's demographic profiles are displayed in *Table 2*. The data analysis was carried out on 133 respondents, 85.7% of the respondents were males and 14.3% were females. About 51.5% of the respondents were between 21 – 40 years old while 38.6% were between 41 – 60 years old. The majority of the respondents were Malay which made up 70.0%, followed by 16.0% Chinese and the rest were Bumiputera Sabah and Sarawak (9.0%), Siamese (4.0%) and Indian (1.0%). The findings showed that the education level of the majority of the respondents was up to secondary (48.1%). This was followed by tertiary level education at 34.6%. Majority (81.2%) of respondents worked as full time farmers. The highest category for monthly income of the respondents was below RM2,000/month (56.8%). There were also respondents with monthly income of more than RM10,000 which accounted for 17.1% whereas the rest of the respondents earned between RM2,000 – RM4,000/month (15.5%), RM4,000 – RM6,000 (10.1%) and RM8,000 – RM10,000 (3.9%). The majority of the respondents (36.4%) had 5 to 6 household members. Most of the respondents involved in this study are experienced farmers as they have been enganged in agriculture for more than 10 years (39.5%).

IoT-based technology usage among farmers

Findings from this study shows that 68.4% of farmers have knowledge about the use of IoT technology in vegetable cultivation in Malaysia (*Table 3*). Most farmers are aware that the use of this IoT system can help in farm management (45.3%). Among other things, 25% of farmers feel that this IoT technology is only suitable for large-scale vegetable cultivation and can help in increasing vegetable production (24.2%). Among the accelerating factors that influence farmers in using this system is the desire to try the latest technology (IR4.0) (31.5%). Government intervention (22.1%) is also seen as an important factor in influencing farmers' decision to use IoT technology. The benefits of IoT systems that can reduce the use of labour (20.5%) and operability (22%) are also factors that may influence farmers in using IoT technology.

Among the farmers who participated in this study (n = 133), 43.6% have used IoT technology in their vegetable cultivation. Among the factors why they use IoT technology is explained in *Table 4*. Majority of farmers (77%) use IoT technology because this technology can facilitate and monitor agricultural activities. On the other hand, among the main reasons why farmers do not use IoT system is because they do not have the opportunity to use this technology (32%) in addition to capital constraints (32%) and being comfortable with conventional methods (23%). This finding shows that most farmers are indeed interested in using this technology. Therefore, government and private agencies need to play their role to help in terms of finance/assistance/incentives as well as promoting the use of this IoT based technology among farmers especially at rural areas.

As mentioned before, 43.6% of farmers in this study have used IoT-based technology for their agricultural activities. Among them are Agriculture applications, IoT sensors and artificial intelligence (AI) based device systems as well as drone/UAV. Details of IoT based technology and crops are displayed in *Table 5*.

Table 2. Socio-demographic profile

	Category	Percentage (%)
Gender	1 = Male	85.7
	2 = Female	14.3
Age	1 = 21 to 40	51.5
	2 = 41 to 60	38.6
	3 = 61 to 80	9.1
	4 = 81 and above	0.8
Race	1 = Malay	70.7
	2 = Chinese	15.8
	3 = Indian	0.8
	4 = Bumiputera Sabah and Sarawak	9.0
	5 = Siamese	3.8
Education level	1 = Primary school	15.0
	2 = Secondary school	48.1
	3 = Tertiary	34.6
	4 = Others	2.3
Job background	1= Farmers (full-time)	81.2
	2 = Government sector	1.5
	3 = Private sector	5.3
	4 = Entrepreneur/retailing	8.3
	5 = Others (including retired)	3.8
Income	1= < RM2,000	53.5
	2 = RM2,000 – RM 4,000	15.5
	3 = RM4,000 – RM6,000	10.1
	4 = RM6,000 – RM8,000	0.0
	5 = RM8,000 – RM10,000	3.9
	6 = > RM10,000	17.1
Household size	1 = 1 – 2	24.0
	2 = 3 – 4	28.7
	3 = 5 – 6	36.4
	4 = < 6	10.9
Experience in vegetable cultivation	1 = < 5	38.0
	2 = 5 – 10	22.5
	3 = > 10	39.5

Source: Field survey (MARDI 2022)

Table 3. Farmers' perception on IoT technology in vegetables cultivation

	Category	Percentage(%)
Farmers knowledge on IoT usage in vegetables cultivation	1 = Yes	68.4
	2 = No	31.6
Farmers perception on IoT technology in vegetables cultivation	1 = Facilitate agriculture activities	45.3
	2 = Increase yield and income	24.2
	3 = Suitable for large scale cultivation	25.0
	4 = High cost	5.5
Promoting factor of IoT usage among farmers	1 = IR 4.0 technology	31.5
	2 = Minimal labour involement	20.5
	3 = Provides privacy and security	3.9
	4 = Interoperability	22.0
	5 = Government intervention	22.1

Source: Field survey (MARDI 2022)

Table 4. Status on IoT technology usage in vegetables cultivation

	Category	Percentage(%)
IoT systems users	1 = Yes	43.6
	2 = No	56.4
Factors for using IoT technology	1 = Remote monitoring for easy management	77.0
	2 = Latest technology	15.0
	3 = Social influence	6.0
	4 = Others	2.0
Factors for not using IoT technology	1 = No opportunity to use the IoT system	32.0
	2 = High cost	32.0
	3 = Comfortable with conventional method	23.0
	4 = Not interested	13.0

Source: Field survey (MARDI 2022)

Factor influencing farmers' behavioral intentions to accept DSS technology. Measurement model

Factor influencing farmers' behavioral intentions to accept DSS technology were analysed using SEM method. The first stage in evaluating the reflective measurement model involves analysing the relationships between the different measures that make up each construct. This is done by using criteria like reliability, convergent validity and discriminant validity (Hair et al. 2016), (Ramayah et al. 2018) and (Hair et al. 2019). The composite reliability (CR) evaluates the consistency and reliability of the measures that constitute a construct and how well they are interrelated. The CR values listed in *Table 6* are within the range of 0.835 to 0.931, which is above the suggested threshold of 0.70. This indicates that the various items measure the same underlying construct consistently and reliable. Provides a concise yet very practical guide in understanding and

Table 5. Type of IoT based technology and crop used by respondents

	Drone/UAV	AI-based equipment and machine	Agriculture applications	Digital timer	IoT Sensor (Including weather, humidity, water quality)	Total (*n*)
Okra	0	0	1	0	2	3
Mushroom	0	0	3	2	2	7
Chilli	0	1	7	0	4	12
Honeydew	0	1	0	0	0	1
Maize	2	0	0	0	0	2
Melon	1	1	4	7	2	15
Salad	0	0	0	0	1	1
Mustard	0	0	0	0	1	1
Brinjal	0	0	2	0	1	3
Cucumber	0	0	1	3	0	4
Tomato	0	0	1	0	0	1
Total (*n*)	3	3	19	12	13	50

Source: Field survey (MARDI 2022)

using PLS structural equation modeling. Convergent validity refers to how well the different measures or indicators of a construct are interrelated and accurately measure the underlying concept.

To evaluate convergent validity, this study will assess factor loadings and average variance extracted (AVE). Factor loadings indicate the degree of correlation between each item and its corresponding construct, while AVE measures the proportion of variance captured by the items in comparison to the total variance of the construct. To establish convergent validity, it is generally recommended that factor loadings should be higher than 0.7 (Hair et al. 2017). While, the AVE value should be no less than 0.5 (Bagozzi and Yi 1988).

Table 6 shows that all the factor loadings for the measures representing each construct were above 0.7, surpassing the suggested threshold for demonstrating convergent validity. Furthermore, all of the AVE values for each construct exceeded 0.5, which is the minimum threshold for assessing convergent validity. These findings indicate that the intended construct were accurately measured and the measurement model has successfully established convergent validity. PEU5, ATT3, ATT4, PB1, PB3, SI4 and TI4 were dropped from the analysis due to low loadings.

Discriminant validity refers to the extent to which measures of different constructs are unique and not highly correlated with one another. To assess discriminant validity, the Heterotrait-Monotrait (HTMT) ratio was evaluated (Henseler et al. 2015). A HTMT ratio value below 0.9 is generally considered acceptable for demonstrating discriminant validity. *Table 7* shows that all correlation coefficients between the measures of different constructs were below 0.9, indicating that discriminant validity was established for the measures in the study.

Table 6. Reliability and convergent validity

Construct	Items	Outer loadings	CR	AVE
Perceived ease of use (PEU)	PEU1	0.879	0.908	0.712
	PEU2	0.899		
	PEU3	0.799		
	PEU4	0.793		
Perceived usefulness (PU)	PU1	0.901	0.903	0.757
	PU2	0.888		
	PU3	0.819		
Attitude (ATT)	ATT1	0.923	0.924	0.859
	ATT2	0.931		
Perceived barrier (PB)	PB2	0.933	0.835	0.632
	PB4	0.722		
	PB5	0.71		
Social influence (SI)	SI1	0.883	0.931	0.819
	SI2	0.931		
	SI3	0.9		
Technology influence (TI)	TI1	0.812	0.879	0.708
	TI2	0.853		
	TI3	0.859		
Behavioural intention (BI)	BI1	0.898	0.907	0.829
	BI2	0.923		

Table 7. Discriminant validity

	PEU	PU	ATT	PB	SI	TI	BI
PEU							
PU	0.704						
ATT	0.773	0.708					
PB	0.109	0.203	0.061				
SI	0.713	0.656	0.624	0.092			
TI	0.517	0.693	0.329	0.579	0.507		
BI	0.753	0.648	0.602	0.232	0.609	0.665	

Structural model

The structural model assesses the proposed relationships between different constructs and involves hypothesis testing. To establish the statistical significance of the proposed hypothesis between the constructs, this study employed the PLS bootstrapping method, which involved using 5000 re-samplings. This study also reported other measures such as the coefficient of determination (R^2), predictive relevance (Q^2), and effect sizes (f^2) to assess the model fit. These measures provide additional information about the strength of the relationships between the constructs and their ability to predict one another.

The results of the hypothesis testing are presented in *Table 8* and it indicates that some of the proposed hypotheses were supported while others were not. The findings indicate that PEU ($\beta = 0.601$, $p < 0.05$) is a significant predictor of PU, which supports H1. Additionally, PEU ($\beta = 0.468$, $p < 0.05$) and PU ($\beta = 0.313$, $p < 0.05$) are significant predictors of BI, which supports H2 and H3. Only ATT ($\beta = 0.249$, $p < 0.05$) and TI ($\beta = 0.304$, $p < 0.05$) are found to be significant predictors of BI, which validates H5 and H8. However, PU ($\beta = 0.093$, $p < 0.05$), PB ($\beta = -0.103$, $p < 0.05$), and SI ($\beta = 0.175$, $p < 0.05$) are not significant predictors of BI, indicating that H4, H6, and H7 are not supported. Since all VIF values were less than 3.3, it indicates that there was no significant multicollinearity issue in the study (Hair et al. 2011).

Structural model assessment

Further to that, as suggested by Shmueli et al. (2019) proposed PLS-predict, a holdout sample-based procedure that generates case-level predictions on an item or a construct level using the PLS-Predict with a 10-fold procedure to check for predictive relevance. Shmueli et al. (2019) suggested that if all the item differences (PLS-LM) are lower (negative value) then, there is strong predictive power, if all are higher

Table 8. Path coefficient and hypothesis testing

Hypothesis		Beta	SE	*t*-values	*p*-values	LL	UL	VIF	Decision
H1***	PEU → PU	0.601	0.063	9.658	0.000	0.467	0.713	1.000	Supported
H2***	PEU → ATT	0.468	0.084	5.673	0.000	0.31	0.639	1.576	Supported
H3***	PU → ATT	0.313	0.091	3.393	0.001	0.143	0.490	1.576	Supported
H4	PU → BI	0.093	0.116	0.846	0.398	-0.137	0.320	2.251	*Not supported*
H5**	ATT → BI	0.249	0.103	2.389	0.017	0.044	0.446	1.755	Supported
H6	PB → BI	-0.103	0.075	1.343	0.180	-0.248	0.051	1.319	*Not supported*
H7	SI → BI	0.175	0.101	1.850	0.065	-0.004	0.376	1.696	*Not supported*
H8***	TI → BI	0.304	0.107	2.801	0.005	0.088	0.506	1.962	Supported

,* significance at α = 0.05; α = 0.01

than predictive relevance is not confirmed while if the majority is lower than there is moderate predictive power and if the minority then there is low predictive power. Based on *Table 9*, only three of the errors for the PLS model were lower than the

Table 9. PLS-Predict

Item	PLS-RMSE	LM-RMSE	PLS-LM	Q^2 predict
ATT1_37	0.811	0.814	-0.003	0.367
ATT2_38	0.723	0.702	0.021	0.397
BI1_56	0.911	0.931	-0.02	0.286
BI2_57	0.839	0.788	0.051	0.437
PU_40	0.84	0.793	0.047	0.334
PU_41	0.876	0.829	0.047	0.267
PU_42	0.932	0.962	-0.03	0.213

LM model thus, it can be concluded that the model has a week predictive power. Furthermore, the Q^2 values are all positive indicated that, the PLS-SEM models offers better predictive performance.

The objective of this study was to explore the acceptance of a DSS for vegetable production among farmers in the selected area. The results of the hypothesis testing revealed that the perceived ease of use (PEU) was a significant predictor of perceived usefulness (PU). Farmers are more likely to adopt a technology if they find it easy to use and it helps them in their daily tasks. A DSS technology that is user-friendly and can provide real-time advice and recommendations can help farmers make informed decisions and improve their crop yield and quality.

Moreover, perceived ease of use (PEU) were also significant predictors for attitude (ATT). When a farmer perceives a technology as easy to use, they are more likely to believe that it will be effortless to integrate into their current farming practices. This, in turn, can increase their willingness to adopt the technology. On the other hand, when a farmer perceives a technology as useful, they are more likely to believe that the technology will benefit them by improving their crop yield, reducing costs, or increasing efficiency. Therefore, when farmers perceive a technology as both useful and easy to use, they are more likely to develop a positive attitude towards the technology and be motivated to use it. This, in turn, increases their intention to adopt the technology for their vegetable production needs.

The results also suggest that attitude (ATT) and technology influence (TI) were significant predictors of behavioural intention (BI). This implies that farmers' attitudes towards the system and their perception of the technology influence their intention to adopt it. If farmers have a positive attitude towards the system and perceive it as beneficial, they are more likely to have a positive intention to adopt it. On the other hand, if farmers have a negative attitude towards the system or perceive it as unreliable or unnecessary, they are less likely to adopt it. Technology influence also plays a significant role in farmers' intention to adopt a smart system. If farmers perceive the technology as innovative and valuable, they are more likely to adopt it. On the other hand, if farmers perceive the technology as complicated or difficult to use, they are less likely to adopt it.

However, perceived barrier (PB), social influence (SI), and perceived usefulness (PU) were not significant predictors of behavioural intention (BI). Farmers may have recognised the potential benefits of using technology, such as increased productivity and efficiency, improved crop quality and reduced labour costs, which may have outweighed the perceived barriers. Additionally, prior experience using technology in their farming practices and social influence from peers and stakeholders in the agricultural sector who were already using the smart system may have also contributed to their positive attitude towards technology and willingness to adopt new innovations. The absence of significance in the role of social influence in the farmers' adoption of the technology suggests that their decision was largely independent of their community's opinions. Agriculture is a highly personalised profession, with farmers having individual production goals and strategies. They may have felt that the adoption of the DSS technology should be based on their own evaluation of the potential benefits and risks, rather than being swayed by others' views. Therefore, the lack of social influence's impact on farmers' adoption of the smart system could be due to their preference for individual decision-making. The lack of significance of perceived usefulness as a predictor of behavioural intention may suggest that farmers were not solely focused on the practical benefits of the system, but also considered other factors such as ease of use and their attitudes towards the technology. Additionally, it is possible that farmers had already recognised the potential benefits of using the DSS, and therefore, their intention to adopt it was already determined regardless of their perceived usefulness.

Conclusion and recommendation

The findings of this study shows that 68.4% farmers are aware of the IoT based system in vegetables cultivation. However only 43.6% farmers have already used the IoT based system, and this may be due to not fully exposed to the technology and cannot afford the technology. In summary, the results of this study indicate that the perceived ease of use, attitude, and technology influence are crucial factors that influence farmers' intention to adopt a DSS for vegetable production. Therefore, efforts should be made to design and develop user-friendly technology that can effectively address the needs and requirements of farmers. Additionally, farmers' attitudes towards the technology and their perception of the technology influence should be considered when promoting the adoption of DSS for vegetable production.

A range of studies have explored the factors influencing the adoption of decision support systems (DSS) in Malaysian agriculture. Adnan et al. (2017) and Omar et al. (2021) both highlight the importance of perceived benefits and ease of use in driving farmers' intention to adopt sustainable agricultural practices and mobile agricultural finance applications, respectively. Churi (2013) and Zhai (2020) further emphasise the potential of DSS in enhancing crop productivity and addressing challenges in agriculture 4.0, such as climate change adaptation and resource allocation. However, there is a need for future research to specifically investigate the acceptance of DSS among Malaysian farmers, considering the unique socio-economic and environmental factors in the country and the cost of IoT's tools, hardware and software which are widely debated of its potential influences towards its acceptance must be considered.

In addition, previous study has shown that behavioural decisions are the result of a combination of individual consideration of their cognition, environmental factors, and expected effects (Ji et al. 2019). The theory of rational behaviour serves as the foundation for the unification of the two studies and is the source of both TPB and TAM. A farmer's awareness is the primary factor that determines their behavioural intention, so while perceived usefulness and perceived is of use in TAM are simply two aspects of their awareness, they also affect farmers' attitudes, which in turn influences farmers' intention to adopt (Dong et al. 2022). Therefore, it is recommended that in the future, the combination of TAM and TPB should be studied because it has been demonstrated that analysing TPB or TAM alone is not as reasonable or scientific as analysing TPB and TAM together (Chih Chung 2013; Hossain et al. 2019).

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Abstrak
Di Malaysia, revolusi pertanian berkembang pesat seiring dengan kemajuan teknologi untuk memaksimumkan produktiviti sambil meminimumkan penggunaan sumber. Selain itu, aplikasi teknologi seperti sistem sokongan keputusan (*Decision Support System*, DSS) boleh meningkatkan kualiti tanaman, mengurangkan kos dan dapat membantu dari segi pengawalan penanaman. Secara teorinya, DSS ialah sistem berasaskan kecerdasan buatan (AI) dan teknologi *Internet of Things* (IoT). Sistem ini menawarkan perkhidmatan perundingan, bantuan teknikal dan khidmat nasihat profesional. Walau bagaimanapun, perbincangan mengenai kebolehgunaan dan penggunaan teknologi ini dan persepsi serta penerimaan petani terhadap teknologi ini amat terhad. Oleh itu, tujuan kajian ini adalah untuk mengenal pasti faktor paling dominan yang mempengaruhi penggunaan DSS dalam penanaman sayur-sayuran di Malaysia. Kajian ini telah mengguna pakai *technology acceptance model* (TAM) sebagai kerangka teori dan *structural equation modelling* (SEM) digunakan untuk menganalisis faktor-faktor yang mempengaruhi penerimaan dan penerimaan DSS dalam kalangan petani. Seramai 133 petani sayur Malaysia terlibat dalam survei ini menggunakan borang soal selidik berstruktur. Dapatan kajian menunjukkan niat petani untuk menggunakan DSS untuk penanaman sayur-sayuran sangat dipengaruhi oleh persepsi kemudahan penggunaan (*perceived ease of use*), persepsi kebergunaan (*perceived usefulness*), sikap dan pengaruh teknologi. Kajian ini menganalisis persepsi dan penerimaan petani terhadap teknologi DSS ini dan dapatan ini dapat digunakan sebagai batu loncatan untuk mewujudkan rangka kerja untuk menambah baik sistem sokongan yang mungkin dapat menangani keperluan petani dengan lebih baik.