Economic and Technology Management Review, Vol. 22(2024): 13 – 30

The acceptance of watermelon cultivation technology among farmers in Malaysia

(Penerimaan teknologi penanaman tembikai di kalangan petani Malaysia)

Norzalila Kasron[1*], Anuar Abdullah[2], Mohd Nur Hafiz Mat Azmin[3], Nurul Nadia Ramli[4] and Nur Fazliana Md. Noh[1]

Keywords: cultivation, SEM, TAM, technology, watermelon

Abstract

Watermelon (*Citrullus lanatus*) accounts for about 8.8% of all tropical fresh fruit production in Malaysia. They are grown, mostly at Kelantan, Pahang, Johor and Terengganu in Malaysia, yielding 92,762 mt in 2021 (DOA 2021). Currently, watermelon cultivation activities such as planting, fertilising, installing plastic mulch and harvesting carried out in Malaysia are conventional, except for land preparation. Therefore, the mechanisation package of watermelon cultivation was introduced to farmers to help simplify and reduce the time of planting activities. The application of these technologies among farmers needs to be empirically measured to identify the factors that influence the adoption of these technologies by employing the Technology Acceptance Model (TAM). The Structural Equation Modelling (SEM) method was used to test the hypotheses in the proposed model. The results showed the positive significant relationship between Attitude with the Perceived Usefulness and Perceived Ease of Use. This shows that technology can be accepted among farmers if it is easy to use and able to give positive impact to farmers. The intervention from authorities such as extension agencies in delivering information and providing training related to technology is important to ensure that technology is used well and optimally.

Introduction

Watermelon (*Citrullus lanatus*) is a flowering plant of the Cucurbitaceae family. It is native to Africa. There are more than 150 varieties of watermelon worldwide and among the famous varieties are Bradford Family, Sugar Baby, Jubilee Bush, Georgia Rattlesnake, Odell's White, Charleston Grey, Mountain Sweet Yellow, Moon and Stars, Ravenscroft and Ledmon where each of these varieties has different characteristics. In Malaysia, watermelon is also known as '*semangka*' or '*timun cina*'. Some varieties used by Malaysian farmers are Princess, Sin Fon, Prime and Boci. Each of these varieties has different characteristics such as seeds, sweetness level and fruit structure.

Watermelon thrives in subtropical or tropical areas where it needs temperatures higher than 25 °C with loose, sandy soil that does not retain water. There are various varieties that farmers often use to grow watermelons, including Princess, Sin Fon, Prime and Boci. Each of these varieties has differences such as the seeds on the fruit, the level of sweetness, and the structure of

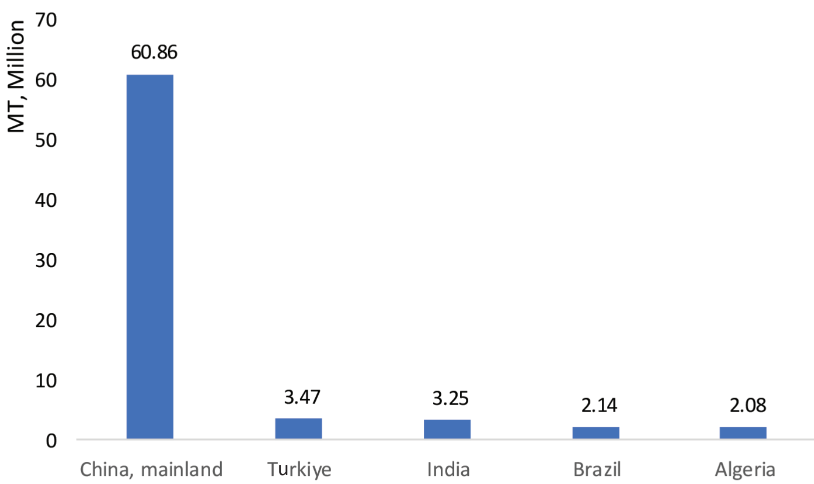
[1]Socio-Economy, Market Intelligence and Agribusiness Research Centre, MARDI Headquarters, Persiaran MARDI-UPM, 43400 Serdang, Selangor, Malaysia
[2]Engineering Research Centre, MARDI Headquarters, Persiaran MARDI-UPM, 43400 Serdang, Selangor, Malaysia
[3]Property Management and Development Centre, MARDI Headquarters, Persiaran MARDI-UPM, 43400 Serdang, Selangor, Malaysia
[4]Agribusiness and Bioeconomic Department, Faculty of Agriculture, Universiti Putra Malaysia
e-mail: norzalila@mardi.gov.my

the fruit. The main watermelon planting season starts from December to March in the eastern part of peninsular Malaysia while April to June is in the northern and southern parts of peninsular Malaysia. Most of the watermelon production operations on the farm involve manual operations. Due to the short period of watermelon cultivation which is only between 65 to 70 days until harvest, watermelon cultivation requires intensive labour, especially during land preparation, plant management and harvest.

In 2021, the total world production of watermelon was 101.635 million mt (FAOSTAT 2022). China is the main producer of watermelon (60.86 million mt) with a market size of 60%, followed by Turkey (3.47 million mt) and India (3.25 million mt) (*Figure 1*). Malaysia is the 57th largest producer in the global ranking with a market share of 0.08% in the same year. The main producer of watermelon is Bachok, Kelantan which contributes the most to the production of watermelon (19.914 mt), followed by Rompin, Pahang (13.386 mt) and Kota Tinggi, Johor (7.684 mt).

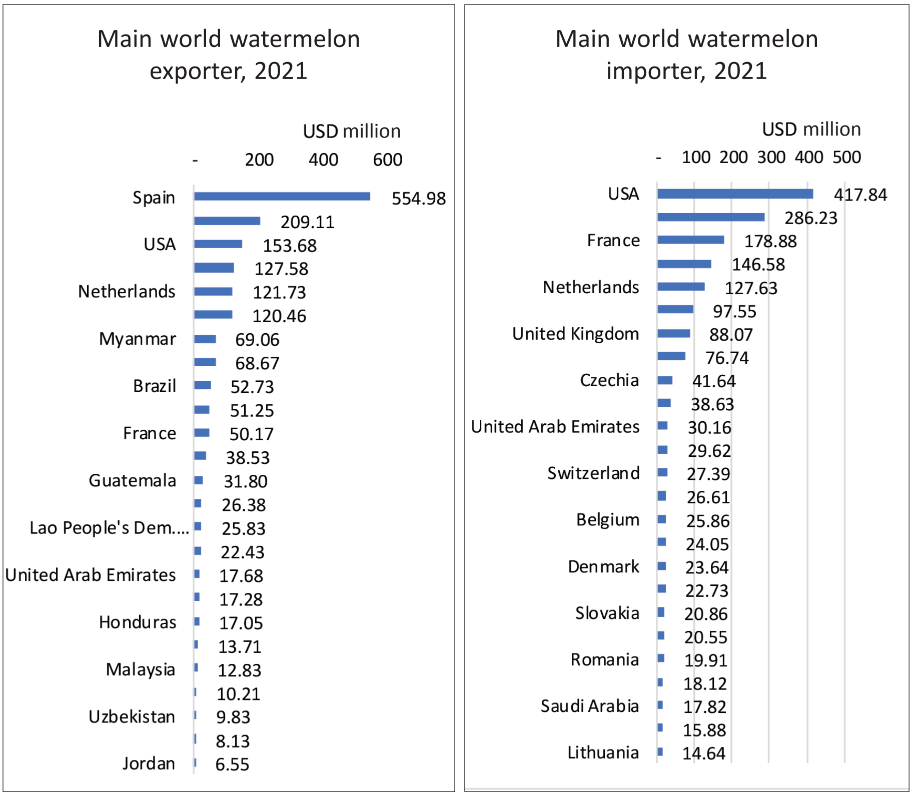
In 2021, the value of world watermelon exports reached USD1.9 billion which is a decrease by 1.23% from 2020. Spain remains dominant (29.0%) in the world watermelon market with the highest export value (USD555 million) followed by Morocco (USD209 million) and the United States (USD154 million). Malaysia is in the 21st position of the world's watermelon exporter, which accounts for 0.6% of the world's watermelon export market (UN Comtrade 2021). While the world's total watermelon imports were recorded at USD2.03 billion where the United States was the largest importer with an import value of USD417.84 million (20.5%), followed by Germany (USD286.23 million) and France (USD178.9 million) (UN Comtrade 2022) (*Figure 2*).

Watermelon production exceeded the self-sufficiency rate of 139.5% in 2021 (SUA2022). In 2021, watermelon production decreased by 4.76%, from 134,225 mt in 2020 to 127,835 mt in 2021. Kelantan is the state that contributes the most watermelon production (39,308 mt), followed by Pahang (23,809 mt) and Johor (15,948 mt) (*Figure 3*).



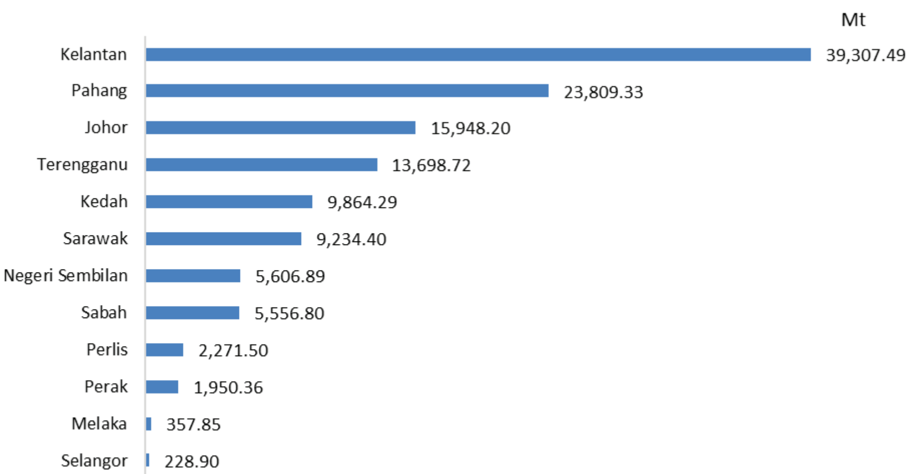
Source: FAOSTAT (2022)

Figure 1. Five main production of world watermelon, 2021



Source: UN Comtrade (2022)

Figure 2. *Main world watermelon exporter and importer, 2021*



Source: Statistik Pertanian (2021)

Figure 3. *Watermelon roduction by state in Malaysia, 2021*

The quantity of watermelon exports from Malaysia showed a decrease of 25% from 60,610 mt in 2019 to 45,324 mt in 2020. Singapore is the main importer with a 93% export share, followed by China (4.5%), and UAE (1.9%). Total imports showed a 27% increase from 5,827 mt in 2019 to 7,394 mt in 2020. (SUA, 2016 – 2020).

Watermelon cultivation in Malaysia predominantly employs conventional methods, with mechanisation limited to ploughing and plant-bed preparation. This reliance on traditional practices persists due to the gradual uptake of new technologies, stemming from a lack of supportive policies, subsidies and requisite training for farmers. The Malaysian Agricultural Research and Development Institute (MARDI) has responded by modifying existing agricultural technologies to align with the specific conditions of watermelon farms in Malaysia. These modifications aim to enhance production efficiency and encompass automatic seeding machines, plastic mulch and irrigation tape layers, planting equipment, mechanical fertilising and weed control systems, harvest aids, and farm waste management machinery. Despite the potential benefits, technology adoption among watermelon farmers remains low. Prior research identifies several impediments to technology adoption, including limited educational attainment, negative perceptions of technology, inadequate capital, small land areas, ineffective infrastructure, and the limited capacity of extension workers (Abu Samah et al. 2009; Hayrol Azril et al. 2009). To facilitate the integration of these technologies, it is imperative to empirically measure their adoption among farmers and to identify the determinants influencing this process. A comprehensive understanding of these factors is essential for developing strategies to overcome the barriers and to support the transition of farmers towards more advanced and efficient farming practices.

Literature review

Planting technology of watermelon

Agricultural mechanisation is the application of engineering principles and technology in the production, control and processing of agricultural products. It involves the use of machines in whole or in part to replace human and animal labour. Mechanisation is not limited to the use of tractors or motorised equipment but also involves any tools that assist in carrying out agricultural activities (DOA 2023).

Developing countries tend to formulate food security development strategies considering the challenges they face in increasing economic growth (Emami 2018). Despite its great importance, technological development in the agricultural industry has lagged far behind other industries. Until today, almost all agricultural industries in developing countries, as well as third world countries, rely on old and conventional ways of agricultural activities. This not only results in low yields for farmers but also creates a huge gap between the supply and demand of agricultural products (Mentsiev 2020). Previous studies have explored ways to increase income in agricultural activities where mechanisation is one of the inputs

Table 1. Planting area, production and trade of watermelon in Malaysia, 2016 – 2021

Year	2016	2017	2018	2019	2020	2021
Planted area (ha)	11,986.8	10,405.8	10,456.8	8,921.5	9,247.4	7,568.3
Production (mt)	192,909.8	172,275.4	150,260.6	144,146.9	134,225.4	127,894.7
Export (mt)	72,023.1	63,046	64,225.9	60,610.7	45,324.3	43,067.9
Import (mt)	4,876.3	4,773.1	3,432.7	5,827.8	7,394.1	6,868.6

Source: Agrofood Statistics (2022); UN Comtrade (2022) that need to be emphasized in increasing agricultural income (He et al. 2016; Yao et al. 2021).

Agricultural mechanisation is the application of engineering principles and technology in the production, control and processing of agricultural products. It involves the use of machines in whole or in part to replace human and animal labour. Mechanisation is not limited to the use of tractors or motorised equipment but also involves any tools that assist in carrying out agricultural activities (DOA 2023).

Agricultural machinery can perform the functions of levelling, land preparation, deep turning and deep scarification (Aslan et al. 2007), which can improve land quality better than the traditional manual and livestock operation methods, especially in the transformation of medium- and low-yield fields (Zhou et al. 2019; Peng and Zhang 2020). Agricultural machinery can increase the degree of multiple cropping of cultivated land to provide the potential for multiple crop cycles per year, thus improving production capacity and land output rates (Peng et al. 2020; Ji et al. 2021). While the use of standardised agricultural machinery can reduce agricultural losses and improve product quality (Qu et al. 2021). Tang et al. (2018) found that the use of agricultural machinery can reduce agricultural production losses, thereby reducing agricultural production costs and promoting high-quality agricultural development.

During the machine performance study, Theoretical Field Capacity (TFC), Effective Field Capacity (EFC) and Field Efficiency (FE) are measured. EFC can be described as the ability of the machine to operate under an actual field condition (Zhou et al. 2012). FE was defined as the percentage of time when the machine is operated at its full rated speed and width in the field (Nasri et al. 2015). FE described how effectively the time was spent to do the work (Grisso et al. 2004). Because of the headland turns, machine trouble, ground surface and overlapping, the FE for an actual field operation was always less than 100% (Zandonadi 2012). The formula that has been adopted to calculate TFC, EFC and FE are as reported by Hanna (2016).

The formulas are:

$$FC = \frac{S\,x\,w}{10} \tag{1}$$

where, s = average speed of the machine, (km/h)
w = rated width of machine, (m)

$$EFC = \frac{A}{t} \tag{2}$$

where, A = total area (ha)
t = total time (hr)

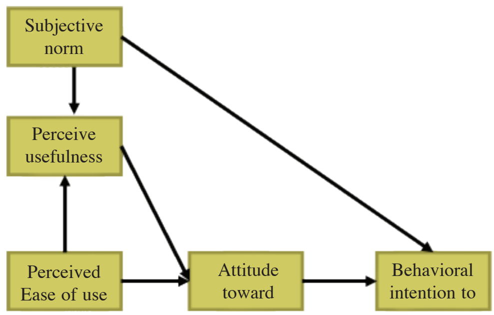
$$FE = \frac{EFC}{TFC}\,x\,100 \tag{3}$$

From the evaluation, the effective farm capacity for each machine can be determined and the data is used to compare the newly developed mechanisation package with the existing methods practised by farmers. Numerically, the use of a mechanization package can reduce up to 263 man-hours/ha compared to conventional operations.

Technology acceptance model (TAM)

TAM was originally proposed by Davis in 1986 and was designed to measure the adoption of new technology based on customer attitudes. It has proven to be a theoretical model in helping to explain and predict user behaviour of information technology (Legris et al. 2003). TAM was predicted by perceived ease of use, perceived usefulness and behavioural intention to measure the acceptance behaviour. Behavioural intention is mainly associated with perceived usefulness and perceived ease of use. Usefulness and ease of use are the important drivers of technology adoption and prior perceptions influence the attitudinal aspect of the behavioural decision (Folorunso and Ogunseye 2008; Kutter et al. 2011; Pierpaoli et al. 2013). It was the intensity of an individual's intention and will to perform the target behaviour (Morris and Dillon 1997). Perceived usefulness is defined as the individual's perception of the extent to which the use of a given technology improves performance that is operationalised based on evidence confirming the effect of system performance expectancy on system usage (Robey 1979). Perceived ease of use is defined as the degree to which a person believes that using a particular system is free of effort (Davis 1989). Subjective norm was added as a new construct which is a direct predictor of behaviour in the Theory of Reasoned Action, which acted as a parental theory for developing TAM, and the Theory of Planned Behaviour (Davis 1989; Ajzen 2011). It is defined as a person's perception that most people who are important think and the behaviour should or should not perform in question (Venkatesh and Davis 2000). This construct was thought to affect intention directly and perceived usefulness (Venkatesh and Davis 2000). Ajzen (2011) justified that subjective norms have a significant direct effect on behaviour if this construct is included in the extended TAM.

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 to agriculture and highlighted the importance of socio-psychological factors as important drivers of technology acceptance and adoption and widely used in agricultural studies (Adnan et al. 2017; Caffaro et al. 2020; Flett et al 2004; Musa 2006; Sammah et al. 2011; Zhang et al. 2009). More studies related to farmers' behaviour 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). Apart from that, TAM has also been applied in agricultural research to explain adoption and use of dairy farming technologies in New Zealand (Flett et al. 2004), to explain the difficulties of precision agriculture technology adoption in Canada (Aubert et al. 2012), to predict the intention to use six grassland management practices on specialist dairy farms in Ireland (Kelly et al. 2015) and to evaluate the main factors influencing grazing technology adoption among new entrant dairy farmers in Europe (McDonald et al. 2016). *Figure 4* shows the TAM that influences farmers' decisions on acceptance of new technology.



Source: Adapted from Venkatesh and Davis 2000

Figure 4. Technology Acceptance Model (TAM)

Materials and method

Data collection

Primary data collection was carried out face-to-face with farmers who cultivate watermelons and a purposive random sampling method was used. The focus of the study location is in Kelantan (Bachok), Terengganu (Setiu) and Pahang (Rompin). Focus group discussion (FGD) was held and farmers were gathered as many as possible according to the location of the study. Structured questionnaires were distributed during FGD. The targeted respondents were 100 however, about 85 responses were obtained during one month (June-July, 2022) survey was conducted. A structured questionnaire was developed with four sections, which are Respondent

Profile (section A), Watermelon Cultivation Information (section B), Awareness of Watermelon Cultivation Technology (section C) and Farmers' Acceptance of Watermelon Cultivation Technology (part D). A Likert scale of 1 to 7 (1 represents strongly disagree while 7 represents strongly agree) was used to measure Farmers' Acceptance of Watermelon Cultivation Technology. Descriptive analysis is used to measure the socio-demographics as an overview of the sample that represents the population by using the frequency of each respondent's demographic variable.

Structure equation modelling (SEM)

Structural equation model (SEM) was used to measure Farmers' Acceptance of Watermelon Cultivation Technology by testing specific hypotheses, as outlined in the conceptual model. SEM is the most statistical method which use in TAM analysis that provides the estimation strength of all hypothesized relationship between variables in a theoretical model (Aggorowati 2012). It also a powerful collection of multivariate analysis techniques, which specifies the relationships between variables using two main sets of equations which are the measurement model and the structural model.

A measurement model measures the latent variables or composite variables (Hoyle 1995, 2011; Kline 2010) and describes the relationships between observed variables and the construct or constructs those variables are hypothesized to measure. while the structural model tests all the hypothetical dependencies based on path analysis (Hoyle 1995, 2011; Kline 2010) and describes interrelationships among constructs. When the measurement model and the structural model are considered together, the model may be called the composite or full structural model. Software IBM-SPSS AMOS was used to conduct a confirmatory factor analysis (CFA), the study employed the maximum likelihood estimation method to minimise the discrepancy in the fit between the estimated population covariance matrix and the observed covariance matrix.

a. Measurement model

The measurement model is the first step to run SEM and is determined through the Confirmatory factor analysis (CFA) which is a factor analysis used to determine whether observed variables have the same characteristics as the other since all the observed variables are undimension. CFA is the fundamental step to verify the measurement quality of all latent constructs that are included in the structural equation model. It was used to assess the unidimensionality, validity and reliability of its measurement model. The analysis can reduce the dimensions, standardize the scale of multiple indicators, and account for the correlations inherent in the dataset (Hoyle 1995; 2011; Kline 2010; Byrne 2013). Items for each latent variable will be verified through a unidimensional procedure to delete items that have factor loading below 0.60. According to Wan Mohamad (2013), any items below 0.60 need to be deleted which indicates less contribution on the variables. The deletion should be made one item at a time and start to delete with the lowest factor loadings. In addition, refer to the high Modification Indices (MI) to identify potential indicators to be deleted or correlated. Zainudin (2015) and Bahaman (2017) also suggest obtaining factor loading for each variable and deleting one item in a sequence (deletion of an item with the lowest loading first). Even though Zainudin (2015) suggested deleting factor loading with a value less than 0.6, Bahaman (2017) recommended deleting factor loading with a value less than 0.5. The Modification Index (MI) value should be checked to reconfirm the wellness of the model and make sure that the fitness index achieves the required level. Correlated errors between items also need to be checked and deleted items one at a time. This step is needed until achieve the model fit. The new measurement model should be re-specified and run after the item is deleted. The process continues until the unidimensionality requirement is achieved (Zainudin 2012).

Test for model fit

The compatibility of the hypothetical models tested is verified using the Fitness Indexes. There is no condition has been stated in the fitness indexes selection that should be reported. However, the use of at least three fit indexes has been suggested by including at least one index from each category of model fit. The three fitness categories are absolute fit, incremental fit, and parsimonious fit (Hair et al. 1998; Holmes-Smith 2006; Wan Mohamad 2013). The absolute fit indices are used to assess the ability of the overall model fit and these indices include the likelihood ratio statistic chi-square ($\chi 2$), in association with root mean square error of approximation (RMSEA), standardised Root mean square residual (SRMR) and the goodness of fit index (GFI) (Hair et al. 1998). The incremental fit indexes are used to compare the proposed model to some baseline model and the incremental fit indices consist of normed fit index (NFI), and comparative fit index (CFI) (Hair et al. 1998; Hair et al. 2006). The parsimonious fit indices are used to investigate whether the estimated model is simpler or can be improved by specifying fewer estimated parameter paths (Hair et al. 1998). The parsimonious fit index includes the adjusted goodness-of-fit index (AGFI). Kline (2010) recommends reporting the chi-squared test, the root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the standardised root mean square residual (SRMR). However, SRMR was not suggested as a model fit indicator due to the small sample size and parameters used in the model (Hooper et al. 2008).

Test for convergent validity

Convergent validity refers to a set of indicators that presume to measure a construct (Kline 2005). Brown (2006) has defined convergent validity as the internal consistency of a set of items or indicators. It represents the strength of relationships between items that are predicted to represent a single latent construct. The items must be strongly related to each other and only represent one factor. To measure convergent validity, factor loading and Average Variance Extracted (AVE) are used. The AVE as a convergent validity test is appropriate since AVE can explain the degree to which items are shared between constructs (Sujati and Akhyar 2020). Hair (2010) and Byrne (2010) suggested the value of factor loading is equal to or more than 0.5 and high-value factor loading indicates high convergent validity. Ahmad (2016) also agreed that the value of AVE must be greater than or equal to 0.5 to attain this validity. Construct with the high AVE indicates a high relationship between items and the construct.

Test for composite reliability

Composite reliability (CR) is the degree to which a test measures what it claims, or purports, to be measuring (Brown 1996). CR is comparable to Cronbach alpha. An instrument with CR higher than 0.7 is considered reliable (Hair et. al. 2010). Kline (2011) has stated that a value of CR that is below 0.5 is considered as not reliable.

Test for construct validity

Discriminant validity is established if a latent variable accounts for more variance in its associated indicator variables than it shares with other constructs in the same model (Fornell and Larcker 1981). It is archived when all redundant items are either deleted or constrained as free parameters. To measure discriminant validity, each AVE value was used by converting to AVE square root and compared with the correlation between the respective constructs. The discriminant validity is achieved when the value of the AVE square root is higher than the value in its row and column.

b. Structural model

The structural model refers to the relationships among latent variables and allows the researcher to determine their degree of correlation (calculated as path coefficients). That is, path coefficients were defined by Wright (1920) as measuring the importance of a given path of influence from cause to effect. Each structural equation coefficient is computed while all other variances are taken into account. Thus, coefficients are calculated simultaneously for all endogenous variables rather than sequentially as in regular multiple regression models.

Maximum Likelihood (ML) estimation is used to test hypotheses about models and parameters. Regression will measure the structural model of the study. The relationship between Perceived Usefulness, Perceived Ease of Use and Subjective Norm were examined to determine the farmer's attitude and intention to continue using this technology.

Six hypotheses were developed before determining the relationship between independent variables (Perceived Usefulness, Perceived Ease of Use and Subjective Norm) and dependent variables (Attitude and Intention) as stated in *Table 2*. These hypotheses were analysed using Structural Equation Modelling Analysis (SEM).

Results and discussion

The demographic profile of respondents shows that 28% of respondents are aged between 31 and 40 years, followed by 27% of respondents who are above 50 years old. A total of 68% of respondents have a secondary high school education. Annual household income in agricultural activities from RM10,000 and below is about 16%, while income between RM10,001 – RM20,000 is 38%. Respondents with the lowest income in agricultural activities are between RM30,000 – RM40,000, which is 13%. Most respondents do not have long experience in the agricultural sector. A total of 32.9% of them have experienced between 6 – 10 years and 28.2% have less than 5 years' experience (*Table 3*).

Table 2. Hypothesis of farmers' acceptance of watermelon cultivation mechanisation package

	Hypothesis statement
H1	The farmer's Attitude towards new technology will affect the farmer's Intention to accept new technology
H2	New technology that helps to increase agricultural yield (Usefulness) will affect the farmer's Attitude
H3	New technology that is easy to use (Ease of use) will affect the farmer's Attitude
H4	The influence of the surrounding people (Subjective norm) has an impact on the farmer's perception of the Usefulness of the new technology
H5	The influence of the surrounding people (Subjective norm) affects the farmer's perception of Usefulness and will affect the farmer's Intention to accept new technology
H6	The easy use of new technology (Ease of use) will have an impact on the farmer's perception of the Usefulness of the new technology

Table 3. Demographics of respondents (n=85)

Variables	Category	(%)
Age	< 20	2.4
	21 – 30	20.0
	31 – 40	28.2
	41 – 50	22.4
	>50	27
Education level	Non-formal education	2.4
	Primary school	18.8
	Secondary school	68.2
	University	10.6
Household income in agriculture activity/year	<10,000	16.7
	10,001 – 20,000	38.1
	20,001 – 30,000	14.3
	30,001 – 40,000	13.1
	>40,000	17.9
Experience in the agriculture field	< 5 year	28.2
	6 – 10 year	32.9
	11 – 15 year	10.6
	16 – 20 year	12.9
	> 21 year	15.3

Structure equation modelling (SEM)

Measurement model

Five latent variables have been identified in the Technology Acceptance Model (TAM) which are Intention, Attitude, Subjective Norm, Ease of Use and Usefulness. All variables were explained by 29 items. Factor loading of all items for the initial assessment was between 0.453 to 0.879. It indicated there are a few items that need to be correlated and deleted since there are high values of MI and low values of factor loading to achieve the model fit. The construct was re-specified and run after eleven items were deleted with factor loading between 0.664 to 0.898 and it met the CFA requirement.

Model fit

This study shows that the value of the fit test model for each Goodness of Fit (GOF) category meets the level of acceptance. The chi-square (SQ) value is less than 0.05. The value of the Root Mean Square Error of Approximation (RMSEA) is 0.066 and meets the condition of the test fit model which is less than 0.08. All indices in GOF such as the Goodness of Fit Index (GFI), Comparative Fit Index (CFI), Turker-Lewis Index (TLI) and Normed Fit Index (NFI) show values that exceed 0.90 and reach the acceptance level. The strength of the fit model value has been confirmed to be eligible to continue the next analysis which is Structural Equation Modelling (SEM). *Table 4* shows three categories of model fit which are Absolute Fit, Incremental Fit and Parsimonious Fit.

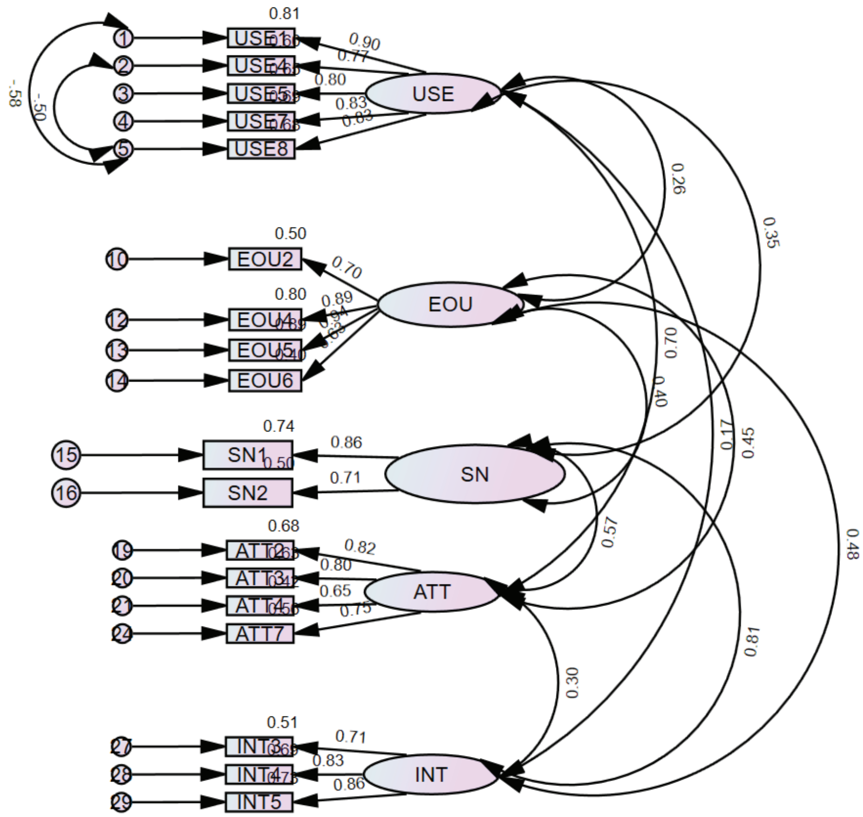


Figure 5. *Technology acceptance's measurement model of watermelon cultivation mechanisation package*

Table 4. Summary of Goodness of Fit (GOF) for farmers' intention on MARDI technology

Category	Index	Acceptance level	Value
Factor loading	Standardised regression weight	Weight > 0.5	All factor loading achieved level of acceptance
Absolute fit	ChiSq	P > 0.05	0
	RMSEA	RMSEA < 0.08	0.066
	GFI		
Incremental fit	CFI	CFI > 0.9	0.952
	NFI	NFI > 0.9	0.907
Parsimonious fit	ChiSq/df	ChiSq/df < 5.0	1.369

Test of validity (convergent validity, construct validity and composite reliability)
The convergent validity test is implemented to ensure that the relationship between all items in each construct is closely related to each other in representing each construct. Average Variance Extracted (AVE) is used to measure convergent validity and the value must be greater than 0.5. The AVE value of this study was between 0.574 to 0.685, which is above 0.5. This high value explains a strong relationship between items and construct. Discriminant Validity is used to ensure that variables are associated with the latent construct being measured. Thus, the measurements are based on the square root of AVE, where the value of AVE2 must be greater than any factor correlation. Discriminant Validity for all constructs is between 0.757 and 0.827 and the correlation between exogenous constructs does not exceed 0.85 which shows that the conditions of Discriminant Validity are met. Composite Reliability (CR) is measured to assess the consistency of each item in the construct where the CR value must exceed 0.5. The findings of this study show CR values ranging from 0.767 to 0.915, which is above 0.5 which indicates that variables well underlying constructs served in structural equation modelling. *Table 5* shows that the validity test has been achieved.

a. Structural model
Table 6 shows the Regression Path Coefficients of Farmers' Intention on MARDI Technology while *Table 7* shows the results of the hypothesis study using SEM. The hypothesis of the research model showed a good fit with the observed data. The path estimates in the structural model and the variance explained in each dependent variable were significant. There are four hypothesised pathways supported at $p<0.001$ while the other two hypothesised pathways are not supported. H1 suggests that Attitude is significantly related to Intention (β: 0.92, t:5.464). Therefore, H1 is supported. Likewise with Usefulness and Ease of Use both variables show that the magnitude of the relationship with Attitude is significant with the respective values being (β: 0.635, t:5.572) and (β: 0.282, t:3.029). It shows that H2 and H3 are supported. Subjective Norm also shows a significant value (β: 0.296, t: 2.14) with Usefulness and this H4 is also supported.

The relationship between Subjective Norm and Intention as well as Ease of Use and Usefulness is not significant with the respective values being (β: -0.179, t:-1.673) and (β: 0.117, t:0.949). If the regression weight is considered, it means that H5 and H6 are not supported.

Table 5. Summary of CFA results for validity test

Construct	CR	AVE	USE	EOU	SN	INT	ATT
USE	0.915	0.685	**0.827**				
EOU	0.862	0.613	*0.382*	**0.783**			
SN	0.767	0.625	*0.350*	*0.545*	**0.790**		
INT	0.843	0.643	*0.173*	*0.530*	*0.712*	**0.802**	
ATT	0.842	0.574	*0.702*	*0.585*	*0.577*	*0.301*	**0.757**

Note: The diagonal represents the square root of the AVE while the italic numbers represent the correlation

Table 6. Regression path coefficient of farmers' acceptance of watermelon cultivation mechanisation package

Construct		Construct	β	S.E	C.R	P	Result
Intention	<--	Attitude	0.92	0.189	5.464	0.001***	Significant
Attitude	<--	Usefulness	0.635	0.149	5.572	0.001***	Significant
Attitude	<--	Ease of use	0.282	0.041	3.029	0.002**	Significant
Usefulness	<--	Subjective norm	0.296	0.079	2.14	0.032*	Significant
Intention	<--	Subjective norm	-0.179	0.16	-1.673	0.094	NS
Usefulness	<--	Ease of use	0.117	0.041	0.949	0.343	NS

Note: *** Significant at 0.001 level
** Significant at 0.01 level
* Significant at 0.05 level
NS Not significant

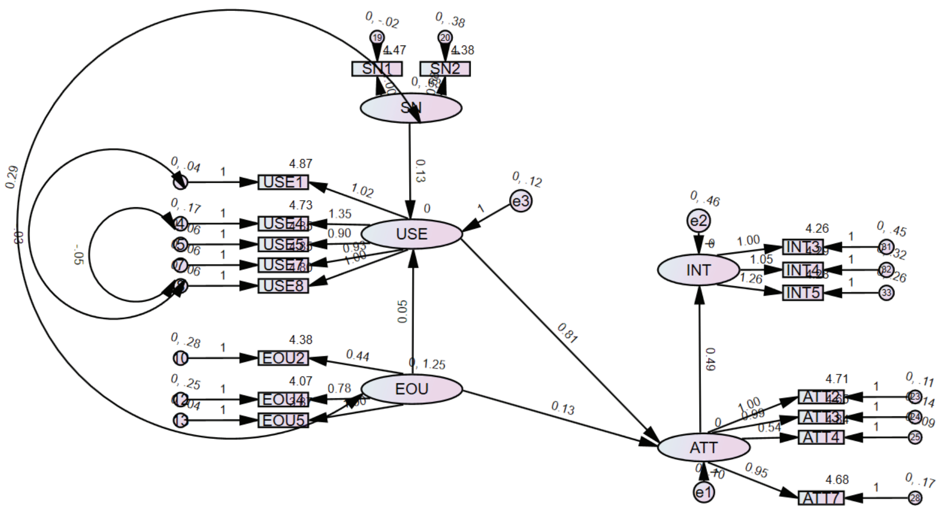


Figure 6: Technology acceptance's structural model of watermelon cultivation mechanisation package

Table 7. Hypothesis of farmers' acceptance of watermelon cultivation mechanisation package

	Hypothesis statement	Result from H_o
H_1	The farmer's Attitude towards new technology will affect the farmer's Intention to accept new technology	H_o Supported
H_2	New technology that helps to increase agricultural yield (Usefulness) will affect the farmer's Attitude	H_o Supported
H_3	New technology that is easy to use (Ease of Use) will affect the farmer's Attitude	H_o Supported
H_4	The influence of the surrounding people (Subjective Norm) has an impact on the farmer's perception of the Usefulness of the new technology	H_o Supported
H_5	The influence of the surrounding people (Subjective Norm) affects the farmer's perception of Usefulness and will affect the farmer's Intention to accept new technology	H_o Not supported
H_6	The easy use of new technology (Ease of Use) will have an impact on the farmer's perception of the Usefulness of the new technology	H_o Not supported

Conclusion

The willingness of farmers to accept the latest technology is a key issue to encourage the use of technology in agriculture. Some important aspects of readiness to use the technologies need to be evaluated to address these issues. The findings indicated that the TAM model constructs with four external factors, which are ease of use, perceived usefulness and subjective norm have a primary role in increasing the acceptance of watermelon cultivation technology. However, only perceived ease of use and perceived usefulness are factors that will influence farmers to use the mechanization package. Farmers are more comfortable if the technology introduced is able in increasing yield, reduce costs and labour and save time on the farm. Currently, the shortage of farm workers and dependence on foreign workers is an issue in the agricultural sector. In relation to that, this problem can be dealt with by using a more efficient and effective planting technology. At the same time, the technology should be easy to operate. This technology can still be used even if the farmer is inexperienced and unskilled in handling it. This positive relationship exhibited that technology that is easy to use and able to have an impact can increase the confidence of farmers to use the technology. Subjective norms are also seen to have a positive significant effect on perceived usefulness. This shows the need for the intervention of extension agencies in deliver the information related the needs and importance of the technology in agricultural activities so that accurate information reaches users and is not misinterpreted. Farmers' high confidence in this technology will in turn increase the intention to use the technology.

Overall, farmers are receptive to the use of new technology if it can reduce time and labour and increase yield. Although the use of technology is often associated with a high price, but with the intervention of extension and research agencies, technology can be channelled to the target group in various methods. Among the methods that have been implemented in Malaysia is renting technologies through service providers. With that, less able and small-scale farmers are still able to use new technology without high investment.

References

Abu Samah, B., Shaffril, H. A. M., Hassan, M. S., Abu Hassan, M. & Ismail, N. (2009). ICT Contribution in Increasing Agro-Based Entrepreneurs' Productivity in Malaysia. *Journal of Agricultural Extension*. 5, 93-98.

Adnan, N., Nordin, S. M. & Bakar, Z. B. A. (2017). Understanding and Facilitating Sustainable Agricultural Practice: A Comprehensive Analysis of Adoption Behaviour Among Malaysian Paddy Farmers. *Land Use Policy*. 68, 372–382.

Aggorowati, M. A., Iriawan, N., Suhartono & Gautama, H. (2012). Restructuring and Expanding Technology Acceptance Model Structural Equation Model and Bayesian Approach. *American Journal of Applied Sciences*. 9(4), 496-504.

Agrofood Statistics (2022). Malaysia: Ministry of Agriculture and Food Industry Malaysia Putrajaya, Malaysia.

Ahmad, S., Zulkurnain, N. N. A. & Khairushalimi, F. I. (2016). Assessing the Validity and Reliability of a Measurement Model in Structural Equation Modelling (SEM). *British Journal of Mathematics and Computer Science*. 15(3), 1-8.

Ajzen, I. (2011). The Theory of Planned Behaviour: Reactions and Reflections. *Psychology and Health*. 26 (9), 1113-1127.

Aslan, S. T. A., Gundogdu, K. S., Yaslioglu, E., Kirmikil, M. & Arici, I. (2007). Personal, Physical and Socioeconomic Factors Affecting Farmers' Adoption of Land Consolidation. *Spanish Journal Agricultural Research*. 5, 204–213.

Aubert, B.A., Schroeder, A. & Grimaudo, J. (2012). IT as Enabler of Sustainable Farming: An Empirical Analysis of Farmers' Adoption Decision of Precision Agriculture Technology. *Decision Support Systems*. 54, 510–520.

Bahaman Abu Samah. (2017). *Structural Equation Modelling using AMOS*. Selangor : Universiti Putra Malaysia

Brown, J. D. (1996). *Testing In Language Programs*. New Jersey: Prentice Hall, Upper Saddle River.

Brown, T. A. (2006). *Confirmatory Factor Analysis for Applied Research*. New York: The Guilford Press.

Byrne, B. M. (2010). *Structural equation modeling with AMOS: basic concepts, applications, and programming* (2nd ed.). New York: Rouledge Taylor and Francis Group.

Byrne, B. M. (2013). *Structural Equation Modelling With AMOS: Basic Concepts, Applications, And Programming*. New York: Routledge.

Caffaro, F., Cremasco, M. M., Roccato, M. and Cavallo, E. (2020). Drivers of Farmers' Intention to Adopt Technological Innovations in Italy: The Role of Information Sources, Perceived Usefulness, And Perceived Ease of Use. *Journal of Rural Studies*. 76, 264–271.

Davis, F. D. (1986). *A Technology Acceptance Model for Empirically Testing New End-User Information Systems: Theory and Results*. Massachusetts, United States: Sloan School of Management, Massachusetts Institute of Technology.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, And User Acceptance of Information Technology. *Management Information Systems Quarterly*. 13 (3), 319.

Department of Agriculture. (2023). Malaysia: Agriculture Engineering. Retrieved from https://www.academia.edu/8128995/KEJURUTERAAN_PERTANIAN_PERTANIAN

Dessart, F. J., Barreiro-Hurlé, J. & van Bavel, R. (2019). Behavioural Factors Affecting The Adoption Of Sustainable Farming Practices: A Policy-Oriented Review. *European Review of Agricultural Economics*. 46(3), 417–471.

Emami, M., Almassi, M., Bakhoda, H. & Kalantari, I. (2018). Agricultural Mechanization, A Key to Food Security in Developing Countries: Strategy Formulating for Iran. *Agriculture and Food Security*. 7 (24),1-12.

FAO. (2022). Rome, Italy: Food and Agriculture Organization of the United Nations. Retrieved from http://www.fao.org/faostat/en/#data

Flett, R., Alpass, F., Humphries, S., Massey, C., Morriss, S. & Long, N. (2004). The Technology Acceptance Model and Use of Technology in New Zealand Dairy Farming. *Agricultural Systems*. 80, 199–211.

Folorunso, O. & Ogunseye, S. O. (2008). Applying an Enhanced Technology Acceptance Model to Knowledge Management in Agricultural Extension Services. *Data Science Journal*. 7, 31–45.

Fornell, C. & Larcker, D.F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*. 27, 39–50.

Grisso, R. D., Kocher, M. F. & Adamchuk, V. I. (2004). Field Efficiency Determination Using Traffic Pattern Indices. *Applied Engineering in Agriculture*. 20(5), 563.

Hair, J. F., Anderson, R. E., Tatham, R. L. & Black, W. C. (1998). *Multivariate data analysis* (5th ed). New Jersey: Prentice Hall, Upper Saddle River.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E. & Tatham, R. L. (2006). *Multivariate data analysis* (6 ed). New Jersey: Prentice Hall, Upper Saddle River.

Hair, J. F., Anderson, R. E., Tatham, R. L. & Black, W. (2010). *Multivariate data analysis* (5th ed.). New Jersey: Prentice Hall, Upper Saddle River.

Hanna, M. (2016). *Estimating the Field Capacity of Farm Machines*. Iowa State University. Retrieved from www.extension.iastate.edu/agdm/crops/html/a3- 24.html

Hayrol Azril, M. S., Md Salleh, H.& Bahaman, A. S. (2009). Level of Agro-Based Website Surfing Among Malaysian Agricultural Entreprenuers: A Case Study of Malaysia. *Journal of Agriculture and Social Science*. 5, 55-60.

He, L. X., Nan, Y. Q. & Zhang, Z. G. (2016). Will agricultural Labor Force Aging Lead to the Decrease of Household's Agricultural Earnings? Based on the Perspective of Village Public Goods Supply. *Journal of Nanjing Agricultural University*. 16, 105–116.

Holmes-Smith, P., Coote, L. & Cunningham, E. (2006). *Structural equation modeling: from the fundamental to advanced topics* (1st ed.). Streams, Melbourne.

Hooper, D., Coughlan, J. & Mullen, M. R. (2008). Structural Equation Modelling: Guidelines For Determining Model Fit. *The Electronic Journal of Business Research Methods*. 6(1),53 – 60.

Hoyle, R. H. (1995). *Structural Equation Modelling: Concepts, Issues, And Applications*. Sage, Thousand Oak

Hoyle, R. H. (2011). Structural Equation Modelling for Social and Personality Psychology. London: Sage.

Ji, Z.-X., Wang, X.-L., Li, L., Guan, X.-K., Yu, L. & Xu, Y.-Q. (2021). The Evolution of Cultivated Land Utilization Efficiency and Its Influencing Factors in Nanyang Basin. *The Natural Resources Journal*. 36, 688–701.

Kamrath, C., Rajendran, S., Nenguwo, N., Afari-Sefa, V. and Broring, S. (2018). Adoption Behavior of Market Traders: An Analysis Based on Technology Acceptance Model and Theory of Planned Behavior. *International Food and Agribusiness Management Review*. 21(6), 771–790.

Kelly, E., Heanue, K., O'Gorman, C. & Buckley, C. (2015). *Proven Science Versus Farmer Perception*. Milan, Italy: 29th International Conference of Agricultural Economists, Agriculture in an interconnected world.

Kline, R. B. (2005). Principles and Practice of Structural Equation Modeling. New York: The Guilford Press.

Kline, R. B. (2010). Principles And Practice of Structural Equation Modelling. New York: Guilford Press

Kline, R. B. (2011). *Principles And Practice of Structural Equation Modeling*. USA: The Guilford Press.

Kutter, T., Tiemann, S., Siebert, R. & Fountas, S. (2011). The Role of Communication and Co-Operation in The Adoption of Precision Farming. *Precision Agriculture*. 12, 2–17.

Legris, P., Ingham, J. & Collerette, P. (2003). Why Do People Use Information Technology? A Critical Review of The Technology Acceptance Model. *Information & Management*. 40(3), 191–204.

McDonald, R., Heanue, K., Pierce, K. & Horan, B. (2016). Factors Influencing New Entrant Dairy Farmer's Decision-Making Process Around Technology Adoption. *The Journal of Agricultural Education and Extension*. 22, 163–177.

Mentsiev, A. U., Amirova, E. F., Afanasev, N. V. (2020). Digitalization and Mechanization in Agriculture Industry. IOP Conference Series: Earth Environmental Science.

Morris, M.G. & Dillon, A. (1997). How User Perceptions Influence Software Use. *IEEE Software*. 14(4), 58-65.

Musa, P. F. (2006). Making a Case for Modifying the Technology Acceptance Model to Account for Limited Accessibility in Developing Countries. *Information Technology for Development*. 12(3), 213–224.

Nasri, N. N., Nawi, N. M., Abdullah, N., Saripa, S. & Mat, R. (2015). Measurement of Field Efficiency for Different Field Operations in Sweet Corn Production. *Proceedings of the Technology and Innovation National Conference*. 1–6.

Paul, L., John, I. & Pierre, C. (2003). Why do People Use Information Technology? A Critical Review of The Technology Acceptance Model. *Information and Management*, 40, 191-204.

Peng, C. & Zhang, C. (2020). Assessment of Agricultural Mechanization on Farmers' Grain Aggregated Production Efficiency. *Journal of South China Agricultural University*. 19, 93–102.

Peng, J. Q., Wu, H. T., Cheng, W. T. & Jiang, F. (2020). Study on the Effect of Mechanization on Farmer's Planting Structure Estimation Method Based on Ivgmm and Ivtobit. *Chinese Journal of Agricultural Resources and Regional Planning*. 41, 55-65.

Pierpaoli, E., Carli, G., Pignatti, E. & Canavari, M. (2013). Drivers of Precision Agriculture Technologies Adoption: A Literature Review. *Procedia Technology*. 8, 61–69.

Qu, X., Kojima, D., Nishihara, Y., Wu, L.-P.& Ando, M. (2021). Can Harvest Outsourcing Services Reduce Field Harvest Losses of Rice in China? *Journal of Integrative Agriculture*. 20, 1396–1406.

Rezaei, R., Safa, L., Ganjkhanloo, M. M. (2020). Understanding Farmers' Ecological Conservation Behavior Regarding the Use of Integrated Pest Management: An Application of The Technology Acceptance Model. *Global Ecology and Conservation*. 22, 1-18.

Robey, D. (1979). User Attitudes and Management Information System Use. *Academy of Management Journal*. 22 (3), 527-538.

Sammah, B. A., Azril, H., Shaffril, M., Hassan, M. A. & D'Silva, J. L. (2011). Can Technology Acceptance Model Be Applied on The Rural Setting: The Case of Village Development and Security Committee in Malaysia. *Journal of Social Sciences*. 7(2), 113–119.

Sharifzadeh, M. S., Damalas, C. A., Abdollahzadeh, G. & Ahmadi-Gorgi, H. (2017). Predicting Adoption of Biological Control Among Iranian Rice Farmers: An Application of The Extended Technology Acceptance Model (TAM2). *Crop Protection*. 96, 88–96.

Statistik Pertanian (2021). Malaysia: Jabatan Pertanian Malaysia Putrajaya, Malaysia

Sujati, H. & Akhyar, M. (2020). Testing the Construct Validity and Reliability of Curiosity Scale Using Confirmatory Factor Analysis. *Journal of Educational and Social Research*. 10,229–237.

Supply and Utilization Accounts (2016-2020). Malaysia: Department of Statistics Malaysia Putrajaya, Malaysia.

Supply and Utilization Accounts (2018-2022). Malaysia: Department of Statistics Malaysia Putrajaya, Malaysia.

Tang, L., Liu, Q., Yang, W. & Wang, J. (2018). Do Agricultural Services Contribute to Cost Saving? Evidence From Chinese Rice Farmers. *China Agricultural Economic Review*. 10, 323–337.

UN Comtrade. (2022). *Trade Statistics*. United Nations: Department of Economic and Social Affairs. Retrieved from https://comtrade.un.org/data/

Venkatesh, V. & Davis, F.D. (2000). A Theoretical Extension of The Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*. 46 (2), 186-204.

Voss, J., Spiller, A. & Enneking, U. (2009). On the Acceptance of Genetically Modified Seed in German Agriculture. *German Journal of Agricultural Economics*. 58(3), 155–167.

Wan Mohamad, A. B. W. A. & Sabri, A. (2013). Modelling a High Reliability and Validity by Using Confirmatory Factor Analysis on Five Latent Constructs: Volunteerism Program. *International Research Journal Advanced Engineer and Scientific Technology*. 1(1),7.

Wright, S. (1920). The Relative Importance of Heredity and Environment in Determining the Piebald Pattern of Guinea-Pigs. *Proceedings of the National Academy of Sciences*. 6, 320-332.

Yao, C. S., Hou, F. G. & Chen, H. Y. (2021). Logical Relation and Its Policy Implications Between Agricultural Mechanization and Food Security: Based on A Contrastive Study of The Cost and Benefit of Three Main Grain Crops Between China and The United States. *Journal of Chinese Agricultural Mechanization*. 42,1–8.

Zainudin, A. (2012). *Structural Equation Modeling Using Amos Graphic*. Shah Alam: Universiti Teknologi Mara Publication Center (UPENA).

Zainudin, A. (2015). *Structural Equation Modeling Using Amos Graphic*. Shah Alam: Universiti Teknologi Mara Publication Center (UPENA).

Zandonadi, R.S. (2012). *Computational Tools for Improving Route Planning in Agricultural Field Operations* (PhD Thesis). Lexington, Kentucky: University of Kentucky.

Zhang, J., Zhang, X., Mu, W., Zhang, J. & Fu, Z. (2009). Farmers Information Usage Intention in China Based on The Technology Acceptance Model. *Computer and Computing Technologies in Agriculture II*. 3, 1845–1853.

Zhou, K., Jensen, A. L. & Bothtis, D. D.(2012). *Simulation Modelling for In-Field Planning of Sequential Machinery Operations in Cropping Systems* (PhD Thesis). Denmark: Aarhus University.

Zhou, Y. B., He, K., Zhang, J. B. & Cheng, L. L. (2019). Growth, Structural and Distribution Effects of Agricultural Mechanization on Farmers' Income. *Journal of Sichuan Agricultural University*. 37, 723–733.

Abstrak
Tembikai (*Citrullus lanatus*) menyumbang kira-kira 8.8% daripada semua pengeluaran buah segar tropika di Malaysia. Buah ini banyak ditanam di kawasan Kelantan, Pahang, Johor dan Terengganu yang menghasilkan 92,762 mt pada 2021 (DOA 2021). Pada masa ini, aktiviti pengeluaran tembikai seperti menyemai, membaja, memasang plastic sungkupan dan penuaian yang dijalankan di Malaysia adalah secara konvensional, kecuali penyediaan tanah. Oleh itu, pakej mekanisasi penanaman tembikai diperkenalkan kepada petani bagi membantu memudahkan dan mengurangkan masa aktiviti penanaman. Aplikasi teknologi dalam kalangan petani perlu diukur secara empirikal untuk mengenal pasti faktor yang mempengaruhi penggunaan teknologi ini dengan menggunakan Model Penerimaan Teknologi (TAM). Kaedah *Structural Equation Modeling* (SEM) digunakan untuk menguji hipotesis dalam model yang dicadangkan. Keputusan menunjukkan hubungan signifikan yang positif antara Sikap dengan kebolehgunaan (*Perceived Usefulness*) dan mudah digunakan (*Perceived Ease of Use*). Hal ini menunjukkan teknologi boleh diterima dalam kalangan petani sekiranya ia mudah digunakan dan mampu memberi impak positif kepada petani. Intervensi pihak berkuasa seperti agensi pengembangan dalam menyampaikan maklumat dan menyediakan latihan berkaitan teknologi adalah penting bagi memastikan teknologi digunakan dengan baik dan optimum.