JOURNAL OF AGRIBUSINESS MARKETING
e-ISSN: 2289-5671
Volume 9, Issue 1, July 2022
DOI: https://doi.org/10.56527/jabm.9.1.4

Open Access

Factors Influencing the Behavioural Intention for Smart Farming in Sarawak, Malaysia

Gabriel Wee Wei En[a]*, Agnes Lim Siang Siew[a]

[a]Faculty of Business, Design and Arts, Swinburne University of Technology, Sarawak Campus, Malaysia

*Correspondence: gwewee@swinburne.edu.my

ABSTRACT:
Agriculture is an industry that contributes to the economic growth and social progress of many countries worldwide, as well as positive impacts to the environment. However, the agricultural industry also faces many challenges, such as the quality of crops and land available for farming activities, climate change, poor economic conditions for farmers, and lack of technology. As the agricultural trend is towards achieving food security, improving nourishment, and advancing sustainable agriculture, Smart Farming harnesses the potential of Industry 4.0 revolution to achieve the goals outlined. The critical consideration would be the intention of farmers to integrate and adopt these smart, connected technologies in their farming activities. This study examined the behavioural intention to use Smart Farming technologies from the perspective of farmers using the Unified Theory of Acceptance and Use of Technology (UTAUT). A cross-sectional study was conducted using quantitative method. Data were derived from farmers in Malaysia via a face-to-face survey in 2021 (n = 381). Partial Least Squares (PLS) regression was applied for model and hypothesis testing. The results indicated that performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) influenced the behavioural intention to adopt SFT. Social influence (SI) was found to be the strongest predictor of behavioural intention. This study contributes to the theoretical understanding of applying UTAUT to examine the behavioural intention to adopt Smart Farming among farmers. In practice, this study also provides implications for the Sarawak government to advance digital inclusion for all communities to achieve high income and advanced status by 2030.

KEYWORDS: Smart Farming, Technology Adoption, UTAUT

MANUSCRIPT TYPE:
Research Paper

PUBLICATION DETAILS:
Received: 7 June 2022
Revised: 30 June 2022
Accepted: 30 June 2022

INTRODUCTION

Agricultural activities range from planting crops (agriculture), timber to raising livestock for household consumption or economic purposes. The agricultural sector performs a crucial role in ensuring the availability of food and achieving food security (Pawlak & Kołodziejczak, 2020). Improved food supply through increased agricultural productivity and expansion of agricultural land use appears to be a viable method of alleviating hunger (Chappel & LaValle, 2011; Pawlak & Kołodziejczak, 2020). Also, agriculture is a source of income for a significant portion of the world's population and nations. In the case of Malaysia, agriculture contributed 7.1% of the country's GDP (RM101.5 billion) and provided 16% of the workforce with employment. Agriculture is the third largest contributor after services (57.7%) and manufacturing (22.3%) (DOSM, 2019). In addition, agriculture is a significant contributor to greenhouse gas emissions (Teschner et al., 2017; Rockstrom et al., 2017). The Intergovernmental Panel on Climate Change (IPCC) reported agriculture sector is accountable for 30 percent of the increase of Greenhouse gas (GHG) emissions. The greenhouse effect keeps the Earth's climate pleasant by maintaining temperature levels, blocking harmful radiation, and maintaining water levels.

However, the development of agricultural production in Malaysia is lagging behind neighbouring countries. One of the causes identified is the availability of land for agriculture. Currently, food crops cultivation is taking up one million hectares of land in Malaysia. However, this is pale in comparison to palm oil cultivation, which has taken up 5 million hectares of land in Malaysia (DOSM, 2020). Das (2015) also shows that land size, fertiliser, and education level have a positive relationship with farmer's income. This is why most rural farmers tend to cultivate and maintain crops only for subsistence due to limiting factors. Although Malaysia's tropical climate, rainfall, sunlight intensity, and soil type have proven to be very suitable for exotic fruits like banana, dragon fruit, durian, etc. Plants are very susceptible to fungal diseases (Ploetz, 2007). Local farmers have to deal with rice blast (rice), moko (banana), and fusarium (tomato) diseases, among others (Strange & Scott, 2005). The precarious and low income of farmers is one factor that has discouraged the younger generation from farming for a living (Masters et al., 2013; Leavy & Hossain, 2014). In Malaysia, only 28% of the population is engaged in agriculture, and on average, they are 60 years old (Noordin, 2018). Alam et al. found that the total annual rainfall in Malaysia is increasing, but the monthly variation is too high. Climate impacts on agriculture include a wide range of attributes and outcomes depending on the specific climate scenario, geographical location, and the nature of the crops. Alam et al. (2011) found that the total annual rainfall in Malaysia is increasing, but the monthly variation is too high. This change will reduce crop yields and are susceptible to drought in many areas, so some crops such as rubber, oil palm, and cocoa will not be able to grow (Murad et al., 2010). A study showed that independent smallholders in Malaysia are less efficient than other producers because of their smaller plots and poor agricultural practices (such as using poor-quality seedlings, keeping old palm trees, insufficient fertilisation, and harvesting immature RFF), and poor practice of data management (Rahman et al., 2008).

The second United Nations Sustainable Development Goal (SDG) commits member states to "end hunger, achieve food security and improve nutrition, and promote sustainable agriculture" (UN, 2015). Unifying the aspirations of communities for nutrition and sustainable agriculture into a single declaration provides a unique opportunity to align the goals of these areas into a common and even ambitious goal. Agricultural innovations are now taking agricultural mechanisation to another level, of concern to farmers, technology providers, politicians, and researchers working in the field. These new technologies on farms are often referred to as Smart Farming Technologies (SFT) - for example, they promise to reduce costs through the application of inputs (fertilisers and plant protection products for animals) according to the actual needs of the soil and of crops, thus reducing the environmental impact of the farm (Basso et al., 2016).

Sarawak, Malaysia's largest state, is located on the island of Borneo, far away from Peninsular Malaysia, and has been seen as a clear disadvantage in terms of development (SCOPE, 2019). In 2020, the agricultural sector contributed approximately 12.1% or 16.5 billion Ringgit to the state's GDP. While Sarawak is still in Industry 2.0, most countries are in Industry 4.0 (Mohammad et al., 2021). Nevertheless, the Sarawak government has embarked on a mission to propel its economy towards introducing intelligent solutions known as Industry 4.0 (SCOPE, 2019). Sarawak also needs to incorporate robotic technologies with artificial intelligence to support the manufacturing sector, particularly for food production and modern agriculture. (SCOPE, 2019). Agriculture is one of the key sectors identified in the economic transformation of Sarawak and plays an important role in alleviating poverty and improving the livelihoods of rural communities. Therefore, there continues to be a need to substantially improve economic growth and development in this sector. The transformation work outlined in the Sarawak Digital Economy Strategy 2018-2022 states that digital technology will be used to create benefits for farmers.

There is now a deep understanding of how SFT can be a solution to the problems above by reducing human intervention through automation (Global Research Alliance, 2014). However, despite the availability of diverse SFT and its significant influence on farm profitability, structure and environmental impact, the adoption of SFT by farmers in developing countries, particularly in Malaysia, remains a challenge. Technical understanding is essential to quantify the benefits and impact of the SFT, and there has been a lot of research exploring the technical and agronomic components of the SFT. However, understanding the non-technical drivers and obstacles farmers face when adopting SFT is essential to understanding how and why farmers make decisions about SFT and what kind of technical, financial or other assistance can enable them to adopt SFT to increase profits and reduce risks. Although there is a growing body of research on the adoption of SFT (Pivoto et al., 2018; Das, Sharma & Kaushik, 2019; Balafoutis, Evert & Fountas, 2020), there was no study done on the adoption of SFT in Malaysia. A critical consideration to the success of SFT is the willingness of farmers to integrate and adopt these smart, connected technologies onto their farms (Zhang et al., 2018). Hence, it is necessary to undertake a study to determine the factors influencing the behavioural intention of farmers in the agriculture value chain so that the development and configuration of SFT meets the demand and specifications of the farmers.

This research aims to fill this gap in the scientific literature by examining the factors that influence the behavioural intention of adopting SFT. Therefore, the findings of this research bear important implications to Sarawak's government, policy makers and smart agricultural developers, and the development of digital solutions to improve agricultural productivity and efficiency, thereby promoting sustainable agriculture and digital inclusion in Sarawak. This research focuses on the factors that have been shown to affect farmers' behavioural intentions, including performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC).

LITERATURE REVIEW / THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

The Development of Smart Farming Technologies in Malaysia

Malaysia is revitalising its agricultural sector by adopting smart farming to improve the productivity and profitability of the industry. The first development of smart agricultural technology in Malaysia was in 1999 with soil properties and sustainable agriculture on precision agriculture. Othman (2012) discovered the development started in 1999 as a result of the Ministry of Agriculture from 1998 to 2010 introducing a third country agricultural policy (NAP3) to promote the adoption of sustainable management in utilising natural resources. The government is also calling for increased use of information and communication technology (ICT) in all sectors to increase productivity (Othman, 2012). Rice is staple food, and despite its high production, Malaysia produced only 80% of its self-sufficiency in 1998 (Lim et al., 2017). Therefore, the development of Malaysia's smart farming technology began with noncultivated precision agriculture to understand the characteristics of soil in order to realise sustainable agriculture.

In 2004, when precision agriculture development peaked, it introduced the concept of water management using irrigation system technology and developed a more comprehensive system than the whole. In 2009, when the Internet of Things technology emerged, research on decision support systems and farm management was conducted to discuss the concept of interconnected systems for decision making. The Internet of Things opens up new possibilities for managing farms through information technology, especially the possibilities of automation (Ibrahim et al., 2018). As a result, research on wireless sensor networks, big data, cloud storage, and mobile phones has emerged as a key component enabling smart agriculture from 2011 to 2019. Integration of smart farming technology not only creates the opportunity for output and quality improvement in agricultural products that meet the market demands, but it also opens up the possibility for ease of market access and distribution of agricultural products in agribusiness (Channe et al., 2015).

Climate change-related development began in 2012 and culminated in 2018 with a focus on sustainable agriculture. The concept of vertical farms emerged in 2018 to introduce urban farming techniques using hydrophobic green materials (Baharudin et al., 2018; Chuah et al., 2019). The Malaysian Department of Agricultural Development has recently launched a pilot program in the deployment of drones for spraying crops in paddy fields over 2,000 hectares. Extending these programs will also need to be reviewed for other crops (Jaabi & Esemu, 2017). This study highlighted concerns about environmental problems caused by agricultural activities and the emphasis on sustainable agriculture as a result of the development of smart farming technology.

The Adoption of Smart Farming Technologies

Having access to a profitable market is another important success factor for the development of the agricultural sector (Singh, 2017). Agricultural digitisation will help farmers in remote areas to access agricultural extension information and advice. They had difficulties before because of the high cost involved and other technological challenges such as limited transfer and usage (Nik Rozana Nik Mohd Masdek et al., 2017). It is highly important to address these issues because not only does agricultural digitisation allows farmers to connect with suppliers, but it also eases the decision-making process in terms of determining the right inputs, technical costs for their operation, inventory management and quality monitoring of the production output (OECD, 2018).

Perceptions of smart agriculture technology vary in developed and developing countries. According to the report, the Australian Institute of Agriculture (2016) report indicates that the adoption of smart technologies and the use of big data in agriculture in the United States is relatively high, especially in the crop sector. More than 40% of corn growers in the United

States produce 70% production on the farm, assisted by smart technology (AFI, 2016). According to Say et al. (2018), the United States is one of the leading countries with innovative farming technology. In addition to the United States, other developed countries like Canada, Australia and some European countries like Germany, Denmark, Sweden and Finland have adopted a number of smart farming technologies.

The author suggests that similar adoption trends are observed in some developing countries such as Argentina, Brazil, Turkey and South Africa. According to Say et al. (2018), more than 80% of Australian farmers use automated guidance and Steele (2017) reported that 98% of farmers in Western Canada also use GPS guidance. Countries that invest the most in research and development (R&D) in smart agriculture (FS) have more publications. Countries such as the United States, Germany, Japan, and South Korea lead the list for their contributions to technological research on smart agriculture by investing more in R&D. In addition, developed countries tend to do more scientific innovation because they invest more in R&D (Pivoto et al., 2018).

The situation in European countries is different from that of other developed and developing countries. Small-scale farms dominate farms in the EU, and interestingly, farm sizes in Europe are much smaller than in the US and Australia. In addition, the growth in farm size in Canada, Argentina and New Zealand was greater than that of farms in the EU. Despite the increase in the use of precision technology by small-scale farms, the CEMA report indicates that only 25% of farmers in the EU have access to precision technology. In addition to this issue, the report also argues that the lack of understanding among smallholder farmers in the EU regarding the correct application of technology will affect them in competing with countries such as Canada, Argentina and New Zealand-Zeeland (CEMA, 2017). There is no research on the application of smart agricultural technology in Malaysia.

Theoretical Background

Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT is the foundation or underpinning theory used in this study to examine the behavioural intention of farmers to adopt SFT in the agriculture sector in Sarawak. UTAUT is a technology acceptance model formulated by Venkatesh et al. (2003). In fact, there are many theories concerning technology adoption; however, UTAUT is one of the most widely used and accepted theories in consumer technology adoption when studying consumer technology adoption (Mohamad & Kasim, 2018).

All the constructs of the technology acceptance theories have been combined and tested by Venkatesh et al. (2003), and unified variables have been proposed to express the effect on user behaviour and behavioural intention of the adopted ICT. The purpose of UTAUT was to identify the variables and mediators that influence individual perception of the adoption and use of ICT and consequently will influence their acceptance. UTAUT integrates eight major user acceptance of technology theories (theory of reasoned action, technology acceptance model, motivational model, the TPB, a combined theory of planned behaviour/technology acceptance model, the model of personal computer use, diffusion of innovations theory, and social cognitive theory) to better describe the research for technology adoption (Venkatesh et al., 2003). The user's intention to use the information system and subsequent usage behaviour is clarified by the theory in which four decisive constructs are affecting the acceptance and usage actions of users in the original theory, namely: performance expectancy, effort expectance, social influence and facilitating conditions (Venkatesh, Thong, & Xu, 2012). Besides, performance expectancy, effort expectancy and social influence are direct determinants of usage intention and behaviour, while facilitating conditions is a direct determinant of user behaviour (Venkatesh, Thong, & Xu, 2012). Previous studies conclude that the four factors have a significant relationship with the adoption of information technology among users (Mohamad & Kasim, 2018).

As the concept and application of SFT remain relatively new to some extent, farmers may not have the notion of whether price value influences their behavioural intention to adopt digital technology. A similar explanation of habit refers to the extent to which individuals automatically perform behaviours because of learning (Venkatesh, Thong & Xu, 2012). All of the additional constructs refer to the actual usage of technologies and play essential roles in determining technology acceptance and use. Furthermore, SFT is yet to be introduced in Sarawak at this stage; hence farmers have little idea about it. Therefore, UTAUT2 with the additional constructs is not relevant for this proposed study.

In addition, existing studies have empirically tested and confirmed that UTAUT outperforms other models by virtue of the excellent robustness of key constructs to predict the purpose and usefulness of some system users (Venkatesh et al., 2003; Park, Yang, & Lehto, 2007; Zhou, 2012; Lu, Papagiannidis, & Alamanos, 2019). Previous studies have extensively used UTAUT to explain the behavioural intentions of ICT adoption in various fields, such as online banking (Martins, Oliveira and Popovič, 2014; Junadi & Sfenrianto, 2015), individual consumer adoption of peer-to-peer mobile payments. (Patil et al., 2020), the adoption of electronic payment systems by university students (Salloum & AlEmran, 2018; Mohammad & Kasim, 2018), and the behavioural intentions of using learning Mobile (Chao, 2019). Recently, Husin, Loghmani and Abidin (2017) conducted a study on the adoption of e-government services in Malaysia, where UTAUT was the underpinning theory. The study indicates that performance expectancy, effort expectancy, and social influence prefigure behavioural intent contributing to IT acceptance.

The study further reports that facilitating conditions and behavioural intention predict the use of behaviour to accept e-government services. A review of the research literature on the Unified Theory of Technology Acceptance and Use (UTAUT) and Technology Acceptance Model (TAM) reveals the strength and flexibility of the variables UTAUT used or considered in the agricultural industry as a tool to capture the impact of Malaysian farmers' adoption of smart agricultural technology factor. Since its inception, UTAUT has been widely used to explain the technology adoption because UTAUT uses the same data to outperform all eight technology adoption models by explaining approximately 70% of variance in behavioural intention (Venkatesh et al., 2003) and 50% in technology use (Venkatesh et al., 2012). As such, UTAUT can provide an ideal mechanism to assess the factors influencing the behavioural intention of farmers to adopt SFT in Malaysia.

Hypotheses Development

Performance Expectancy

In an agricultural context, notions of increased productivity and time savings have often been retained (Engotoit et al., 2016; Far & Rezaei-Moghaddam, 2017), while increased profits have also been incorporated (Ronaghi & Forouharfar, 2020). Michels et al. (2020) also supported performance expectancy as having a positive effect on the behavioural intention to use a crop protection smartphone app among German farmers. The root constructs of performance expectancy incorporate relative advantage, perceived usefulness, and outcome expectation (Venkatesh et al., 2003). Thus, performance expectancy is close to the perceived usefulness variable within TAM, which, because it is stable, efficient, and parsimonious, has become the

most widely adopted method for predicting technology usage (Palau-Saumell et al., 2019). Some studies have widened the definition to include how the practice aids farm management (Engotoit et al., 2016). General notions of whether the practice improves farm management (Duang-Ek-Anong et al., 2019) and whether it is better than what it replaces, or is essential to farming needs (Beza et al., 2018), have sometimes been included.
The proposed hypothesis is as follows:

$H_0$1: *There is no relationship between Performance Expectancy and Behavioural Intention to adopt SFT for farming purposes.*
H_a1: *There is a relationship between Performance Expectancy and Behavioural Intention to adopt SFT for farming purposes.*

Effort Expectancy

In the context of this study, EE reports that farmers consider and evaluate the potential effort required to adopt SFT. They then determine if the efforts required are in line with the benefits of adopting the technology. In addition, previous empirical research on mobile app adoption has supported the belief that EE influences intention to use. In addition, the relationship between EE on behavioural intention has been shown to be significant (Moore & Benbasat, 1991; Thompson, Higgins, & Howell, 1991; Chao, 2019). For example, EE has a positive impact on PE when users think that SFT is relatively easy to use, requiring little effort to achieve the desired performance. (Zhou, Lu, & Wang, 2010). When consumers perceive greater effort to use innovative technology, their tendency to use the technology decreases (Zhou, 2011). Junadi and Sfenrianto (2015) also demonstrated that EE has a positive influence on the intention to use the farming system, while Michels et al. (2020) suggested that EE has a positive effect on the intention to use the crop protection application on the smartphone of farmers in Germany. In this study, the ease of use of the digital platform led to farmers' willingness to use the application.

The proposed hypothesis is as follows:

$H_0$2: *There is no relationship between Effort Expectancy and Behavioural Intention to adopt SFT for farming purposes.*
H_a2: *There is a relationship between Effort Expectancy and Behavioural Intention to adopt SFT for farming purposes.*

Social Influence

Agriculture is not only an economic activity but also a socio-cultural activity (Rasheed & Mahmod, 2018). The pressure generated by social interactions and norms can motivate farmers to adopt SFT. In the context of this study, social influence is operationalised as being persuaded (informed) to use smart agricultural techniques in agriculture by faith-based groups, community members and peasant groups. Therefore, it can be assumed that the social influence on the use of SFT influences the farmers' intent to adopt it.

The proposed hypothesis is as follows:

$H_0$3: *There is no relationship between Social Influence and Behavioural Intention to adopt SFT for farming purposes.*
H_a3: *There is a relationship between Social Influence and Behavioural Intention to adopt SFT for farming purposes.*

Facilitating Conditions

Previous studies in the context of technology adoption show that FC had a positive effect on behavioural intentions to use information systems (Jong & Wang, 2009; Lakhal, Khechine & Pascot, 2013; Moore & Benbasat, 1991; Venkatesh et al., 2003; Venkatesh, Thong and Xu, 2012). To run internet banking, users must have certain skills in configuring and operating computers, connecting to the internet, etc. (Martins, Oliveira & Popovič, 2014; Rahi et al., 2018). Putri (2018) also indicated that FC had a positive impact on e-payment adoption. Lee & Heo (2020), Li et al. (2020) and Ronaghi & Forouharfar (2020) also showed correlations between FC with the behavioural intentions of farmers employing smart farming technologies. The proposed hypothesis is as follows:

$H_0$4: *There is no relationship between Facilitating Conditions and Behavioural Intention to adopt SFT for farming purposes.*
H_a4: *There is a relationship between Facilitating Conditions and Behavioural Intention to adopt SFT for farming purposes.*

METHODS

Research Design

This study is purposed to examine the relationship between various factors of UTAUT (performance expectancy, effort expectancy, social influence and facilitating conditions) and the behavioural intention to adopt SFT. Thus, the research design utilises a quantitative approach where the data collected is aimed to analyse, interpret and achieve the study objectives in order to validate or refute the hypotheses. In addition, causal research methods are adopted as it aims to examine underlying conditions of cause-effect relationships among constructs. The use of the quantitative approach, which is the nature of causal research, allows higher levels of reliability in data collection through its ability to quantify data to support or refute alternative knowledge claims (Apuke, 2017; Taguchi, 2018).

Sampling Design

This study focused on Sarawak, as Sarawak was the highest contributor to the national agriculture sector in 2016 (DOSM, 2019). Hence, examining the behavioural intention of the farmers in Sarawak could be one of the positive steps in leading the agriculture transformation as part of the Sarawak Digital Economy Strategy for 2018-2022. Using the approach of Krejcie and Morgan (1970), a sample size of 384 with a confidence level of 95% and a significance level of 5% was sufficient for a total population size of over 1 million. At the time of this study, the estimated population of farmers in Sarawak was estimated to be around 174,059 (Sarawak Facts and Figures Portal, 2016). This indicates that the sampling size can vary from a minimum of 85 for performing correlation analysis to a maximum of 384. Using cluster random sampling method, the total population of farmers in Sarawak were divided into 12 clusters, represented by the divisions. Applying equal allocation technique, 130 farmers were selected from three divisions within the scope of the study (Kuching, Samarahan and Serian), generating a total sample size of 390. The name list was randomly selected by the respective area leader of the AFO. This study used a personally administered questionnaire survey method by researchers to select, distribute, and collect surveys and drop off and pick up survey methods for their convenience, response rate and time. The procedure began with a name list randomly selected by the respective area leader of State Farmer's Organization Sarawak (PPNS) from Kuching, Serian and Samarahan. The researcher, along with the area representative, administered the questionnaire to the selected farmers.

Research Instruments

As the research uses a quantitative approach, data collection is conducted with the use of a self-administered online questionnaire to examine the conceptual model of this study. It captures the responses of each respondent mainly based on closed-ended questions using a seven-point Likert-type scale where the respondents can select from a list of choices from 1 (strongly disagree) to 7 (strongly agree). This allows higher effectiveness of data collection as it helps to increase response rate by fastening completion time and reducing the drop-out rate of responses (Desai & Reimers, 2019; Ho, 2017). Moreover, it eases the researcher's analysis of the data collected as it is normative and easy to administer based on the scale, as well as allowing higher reliability and validity of results at a later stage of the research (Taherdoost, 2019; Hair, Howard & Nitzl, 2020).

Items were adapted from previous studies to decipher each category of constructs involved in the study. This involves PE, EE, SI, and FC under the Unified Theory of Acceptance and Use of Technology (UTAUT) as adopted from studies regarding the use of SFT. The items from BI are adopted to explain factors that influence respondent's responses based on established studies. The selected measurement instruments are appropriate as composite reliability and validity, with values between 0.700 to 0.900 and values above 0.500, respectively, have been established in each study.

Data Analysis

The data collected are imported into the Statistical Package for Social Science (SPSS) 26.0 and Smart-PLS 3.0 for further analysis. To analyse the hypotheses, a variance-based structural equation modelling (SEM) approach, which is known as the Partial Least Squares structural equation modelling (PLS-SEM), is deployed to test the prediction of various antecedents-to-consequences path relationships (Hair et al., 2021; Sharma, Pohlig & Kim 2017). Thus, it enables the inclusion of latent constructs in the study, which are measured by manifest variables or items, allowing higher reliability and accuracy of data analysis (Hair, Ringle & Sarstedt 2011). Quantitative research techniques commonly face non-response errors during data collection (Queirós, Faria & Almeida 2017; Priester, Petty, & Park 2007). It becomes crucial to ensure that the data collected are complete and they fulfil the requirements of the study. Hence, the preliminary data analysis stage includes screening and filtering the collected data to be used. This includes analysing the data based on the response rate and quality as collected from the statistics of results provided from Survey Monkey, which is then manually analysed to ensure that there is an equal representation of respondents to support the subsequent decision on hypotheses. To continue from there, the SPSS 26.0 software system is used to perform a descriptive analysis on the respondents to examine their relationship and the descriptive statistics, which includes the mean and standard deviation with the instrument items to be tested.

Descriptive analysis consists of three types of descriptive statistics, which include frequency, central tendency, and dispersion or variation (Kaliyadan & Kulkarni, 2019; Mishra et al., 2019). This study analyses the data by exploring the frequency and meaning of certain characteristics of factors. Frequency is determined from the sum of all occurrences, which this total number of data set divided by the total number of elements involved in the category (Ong & Puteh 2017; Kaur, Stoltzfus & Yellapu 2018). As the frequency is used for categorical data, the measurement shown as the frequency in this study is the respondents' demographic profiles as it determines each profile of respondent (Mishra et al., 2019). The mean score is also used to identify the independent and dependent indicators.

The measurement model assesses the reliability of individual items, internal consistency between items, the model's convergent and discriminant validity to indicate the acceptability of the model where certain indicators are required to be met (Gu et al., 2019). These include items loading to be above 0.700, composite reliability to be between 0.600 to 0.900 and average variance extracted to be 0.500 and higher in order to meet the required thresholds of the data. Additionally, discriminant validity is established through the use of Fornell and Lacker's criterion and cross-loading analysis.

The Partial Least Square Approach to Structural Equation Modelling (PLS-SEM) is used to analyse the causal relationships within different latent factors of the respondents' actual purchase of using e-discounts on food delivery services. This method is applied as the PLS-SEM model can investigate causal relationships between various factors (Ong & Puteh 2017; Chin et al. 2020). While to ensure reliability and validity, the model's predictive strength and quality of the PLS-SEM measurement are checked by assessing various components (Hair et al., 2021). First, the lateral collinearity (VIF) identifies the presence of hidden later collinearity with a threshold below 3.000 as to be accepted in the study (Hair et al. 2019). Next, the coefficient of determination (R2) uses the level of variances explained on endogenous constructs to describe the explanatory power of the model. The predictive relevance (Q2) assesses predictive power through the blindfolding procedure that contributes to evaluating out-of-sample predictions (Sarstedt et al., 2017; Shmueli et al., 2019). Effect size ($f2$) is also included to further assess the predictive impact of exogenous constructs. Lastly, to determine the relationships between various constructs, the significance of path coefficients including critical value (t-value) and probability (ρ-value), are analysed through PLS bootstrapping procedure (Hair et al., 2019; Sharma, Pohlig & Kim, 2017).

RESULTS

The demographic distribution of the respondents is presented in Table 12, it shows that 71.4% of the respondents were male while 28.6% were female. Considering the age of the respondents, 5% were aged below 18 years, 21% between 18–24 years, 21.3% between ages 25–44, 48% between ages 45–64, while 4.7% were those above 65 years. The largest proportion was composed of those aged between 25-44. Considering the education of the respondents, 23.1% with primary level, 47.2% with secondary level, 8.4% with certificate/diploma, 4.2% with Bachelor's degree, and 17.1% with no education background. The largest proportion was composed of those with secondary level education. Another aspect examined was the farm size and the type of farming. Considering the farm size of the respondents, 73.8% with less than 10 hectares, 22% with 10-50 hectares, 2.1% with 51- 100 hectares and 2.1% with more than 100 hectares. The largest proportion was composed of those with less than 10 hectares. Considering the type of farming, 35.2% was arable, 4.2% was pastoral, 11.5% was mixed, 10.5% was subsistence, and 38.5% was commercial. The largest proportion was commercial farming. When asked if Information Technology (IT) can make farming easier, 69.6% of the farmers indicated Information Technology (IT) could make farming easier, whereas 30.4% of the farmers indicated Information Technology (IT) could not make farming easier. The largest proportion was the farmers who think Information Technology (IT) can make farming easier. When asked where the farmers get information about new technology in farming, 55.9% was from social media, 11.6% from search engine, 9.7% from TV, 8.7% from print, 7.9% from radio, 4.2% from word of mouth, and 2.1% from the exhibition. The largest proportion was getting the information about new technology in farming from social media.

Table 1: Measurement Model Results

Construct	Indicator	Loading	Cronbach's Alpha	Composite Reliability	AVE
Performance Expectancy (PE)	PE1	0.881	0.881	0.919	0.739
	PE2	0.872			
	PE3	0.889			
	PE4	0.794			
Effort Expectancy (EE)	EE1	0.903	0.933	0.952	0.833
	EE2	0.925			
	EE3	0.916			
	EE4	0.906			
Social Influence (SI)	SI1	0.898	0.879	0.918	0.739
	SI2	0.904			
	SI3	0.898			
	SI4	0.727			
Facilitating Conditions (FC)	FC1	0.773	0.833	0.889	0.667
	FC2	0.844			
	FC3	0.876			
	FC4	0.770			
Behavioural Intention (BI)	BI1	0.927	0.935	0.954	0.839
	BI2	0.933			
	BI3	0.937			
	BI4	0.863			

The factor loadings of all items are higher than the threshold value of 0.7, confirming the good reliability of the tool indicators (Table 1). In this study, no measurement items needed to be dropped. All the constructions showed composite reliability (CR) and Cronbach's α values greater than 0.7, indicating that the construction reliability standards were met. The AVE of all structures is greater than the minimum acceptable value of 0.5, confirming that the convergence validity standard is reached. In order to verify the reliability of latent variables, CR and AVE must be higher than 0.8 and 0.5, respectively. The reliability of both is acceptable and clearly confirms the reliability of the model measurement.

The coefficient of determination is a measure of the model's predictive power and is measured as the square correlation between the specific and predictive values of a given endogenous construct. The higher value of R square (R^2) indicates higher levels of predictive accuracy. The rule of thumb for obtaining appropriate R^2 values is challenging since it depends on the complexity of the model and the research discipline. In scholarly research that concentrates on marketing issues, R^2 values of 0.75, 0.5 and 0.25, respectively, are described as substantial, moderate, or weak (Hair et al., 2011; Henseler et al., 2009). The R^2 in this study was 0.618, which falls under moderate predictive accuracy. The values of the inner and outer model (Figure 1) present the path coefficients and significance level (bracketed). The value of R Square is within the construct.

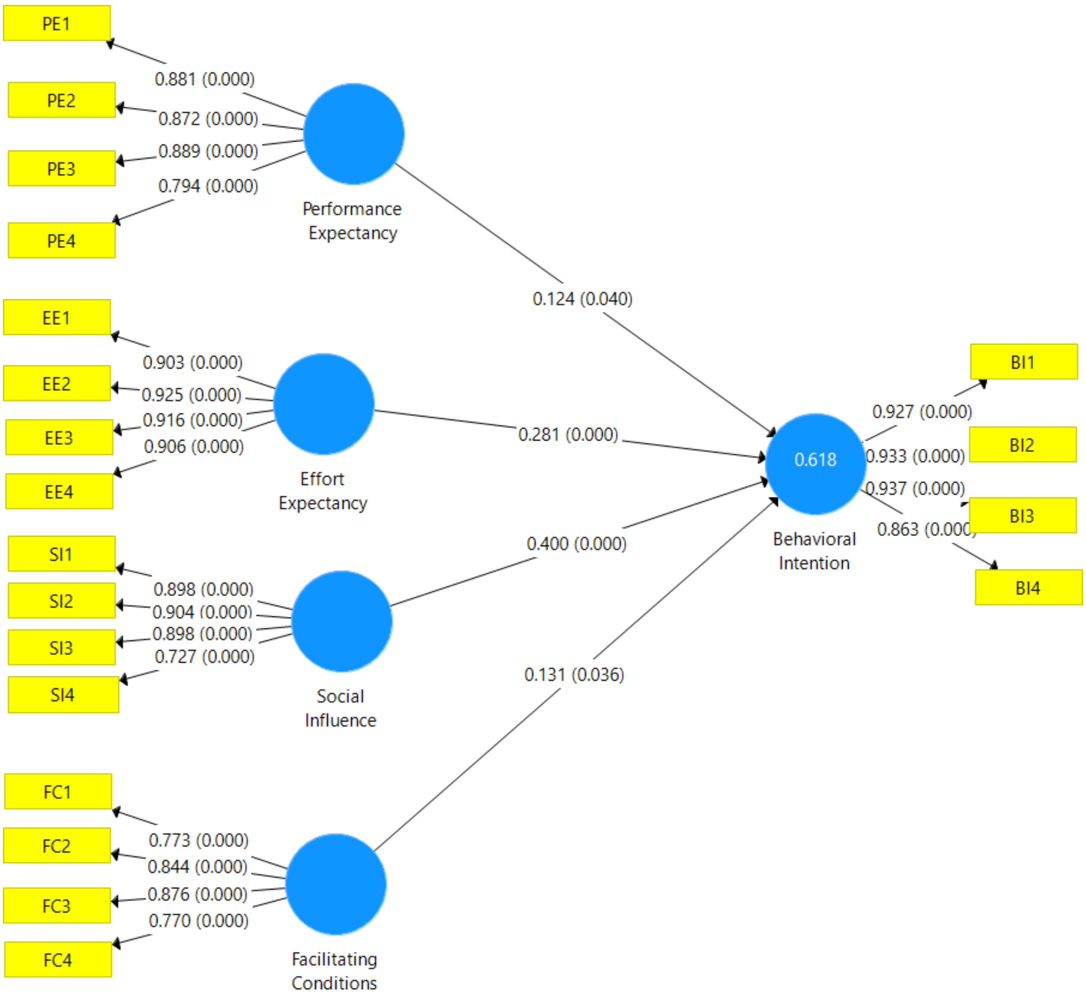

Figure 1: Results of the PLS analysis

This study focused on examining the factors influencing the behavioural intention for smart farming in Sarawak. The evaluation of the hypothesis and whether the hypothesis testing can reject or fail to reject the hypotheses after conducting the data analysis is presented in Table 2 below. Hypothesis testing in the context of PLS-SEM is usually conducted through the calculation of the P value for each path coefficient. The P-value is the probability that would have found the current result if the correlation coefficient were, in fact, zero (null hypothesis) (Goodman, 2008). The standard value chosen for level of significance is 5% (P = 0.05). If this probability is lower than the conventional 5% (P < 0.05), the correlation coefficient is called statistically significant. A statistically significant test result ($P < 0.05$) means that the test hypothesis is false or should be rejected (Davis & Mukamal, 2006).

Table 2: Evaluation of Study Hypotheses

Hypothesis	Construct	*p*	Result
H01	**PE -> BI**	0.040	Supported
H02	**EE -> BI**	0.000	Supported
H03	**SI -> BI**	0.000	Supported
H04	**FC -> BI**	0.036	Supported

DISCUSSIONS

This discussion is drawn from the impact of the antecedents of the Unified Theory of Acceptance and Use of Technology (UTAUT) on the behavioural intention to adopt SFT in Sarawak. The present findings concluded that four hypotheses were supported (H_01, H_02, H_03 and H_04). Thus, it highlights the effect of UTAUT as a significant factor towards farmers' behavioural intention for SFT, particularly how Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Condition have a significant effect towards the Behavioural Intention to adopt SFT. Social Influence was found to have the strongest relationship with Behavioural Intention.

IMPLICATIONS

Theoretical implications

The main theoretical implication is the application of the UTAUT in explaining the adoption of smart farming technology in the agriculture sector. Furthermore, this study offers further theoretical support relating to the role of performance expectancy, effort expectancy, social influence and facilitating conditions in the adoption of SFT. The first theoretical implication of this study aims to fill the research gap in the application of UTAUT in explaining the behavioural intention of farmers to adopt SFT in the agriculture sector in Sarawak. This study is significant because it integrates the UTAUT to predict and explain the behavioural intention of using SFT.

The results of this research indicate that the direct relationships (PE, EE, SI, and FC) respectively related to the adoption of SFT are all positively and significantly associated. Similarly, the results confirm that PE, EE, SI, and FC are the antecedents to the behavioural intention of farmers to adopt SFT. Additionally, prior studies seldom focused on the use of Industry 4.0 technologies in the agriculture sector. By including the farmers in this research, it offered a more holistic understanding of smart farming technology adoption in the agriculture value chain. As the study is based on the Sarawak context to assess the behavioural intention of farmers in the agriculture value chain towards smart farming technology, it also offers further theoretical support regarding the role of PE, EE, SI, and FC in the adoption of SFT. As SI has the strongest beta, it shows that the farmers in Sarawak are easily influenced and led by their peers.

Managerial implications

The findings of this research provide important implications from both a practical perspective and purpose. SFT indeed benefits the Sarawak government as well as agriculture stakeholders such as farmers, suppliers, distributors, hardware and software developers. Furthermore, this study aligns with the Sarawak Government's agenda to digitise the state's economy, and so the findings are of significance to the Sarawak government, policymakers, digital solution providers and users in developing the overall robust smart farming system and platform optimised for Sarawak agriculture sector. Additionally, the current study is both relevant and timely since it focuses on the use of smart farming technology in the agriculture sector and is identified as one of the priority sectors in the Sarawak digital economy ecosystem.

Since PE is reported to have a significant impact on behavioural intention, digital solution providers and the government should direct their attention to PE of SFT in order to boost the adoption rate. It is also believed that the intention to adopt tends to be higher when SFT is demonstrated to provide more features or functionality to perform daily activities that aid the lifestyle of farmers. For example, the user-friendliness' of the SFT would enable farmers to find SFT easy to access and understandable. The farmers who participated in this study believed that SFT could help them to accomplish their tasks quickly and in generating a higher income with better quality and quantity of yield. Therefore, the PE of the SFT is important towards the widespread adoption of the technology.

Moreover, digital solution providers and the government should consider the operation and design of SFT. Most farmers in Sarawak do not have a high educational level but are willing to learn and follow the trend in an urban area where the smartphone and internet play a key part in their daily life. Since EE is reported to have a significant impact on behavioural intention, the design of the SFT is relatively easy and understandable from the farmers' perspective. This would further help to lead to increasing the number of farmers accepting the SFT in the future.

Social influence (SI), as highlighted in this study, is the most important antecedent, which coincides with the findings by other researchers in the same field. Given that SI is reported to have a significant impact on behavioural intention, digital solution providers, the government, and respective boards should consider organising training, talks or campaigns for the community prior to the introduction of SFT. The head of the community, known as the head of the longhouse (Tuai), plays an important role in leading the farmers' behavioural intention. The community leader may also request respective boards or third parties to provide talks or involvement in campaigns on the concept of SFT to showcase the application and function of the internet in urban daily lives, including the advantages and risks of adopting digital technologies in the daily lives of the farming community in Sarawak. The pressures created by social interactions and norms may motivate farmers in the uptake of SFT. Opinions shared by friends, relatives and superiors are rather influential to farmers. Therefore, SI acts as the main antecedent in technology adoption.

Moreover, given the fact that FC influences the behavioural intention of farmers towards the adoption of technology, the Sarawak government should consider speeding up the process of building the necessary infrastructure, such as access to high-speed internet in rural areas. Accordingly, this study supports the development of appropriate infrastructure by the government that aligns with the objectives set by the government under the Sarawak digital economy initiative to satisfy the needs of farmers to adopt SFT. One of the objectives is to optimise the utilisation of existing and new telecommunication and network infrastructure, in addition to increasing broadband coverage and upgrading its speed and reliability. Notably, the need to improve the surrounding infrastructure is aligned with Action 33, as stated in the government's digital strategy to provide affordable and high-speed internet access for the masses through carrier-independent backhaul and backbone data transmission services. The Sarawak government should also continue to monitor the progress of building communication towers in those areas where the government plans to target building 600 telecommunication towers in the state.

CONCLUSION

This research examined the factors influencing the behavioural intentions of farmers to adopt SFT in Sarawak. In order to attain the research objectives, a questionnaire survey was used to collect data from several divisions in Sarawak. The research also carried out a comprehensive literature review on the theories of UTAUT. Four research questions, along with four hypotheses and the conceptual framework of this study, were developed. All the paths in the research model were discovered to be significant in the context of this study. The findings showed that performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) played a significant role in the behavioural intention to adopt SFT.

As the progress of the government in Sarawak progresses towards a wider utilisation of digital technology to advance the agriculture industry and economy in Sarawak, the government and respective boards need to collaborate in leading farmers towards digitalisation. Overall, the findings of this study are anticipated to be helpful for the Sarawak government, policymakers, and digital solution providers, in addition to users in the agriculture sector, in identifying the needs of farmers and develop SFT where the functionality of these technologies suits the local specification. Finally, there is a distinct, if not a high possibility, that Sarawak can advance towards achieving digital inclusivity for all communities contributing to the state's economic growth and development by 2030.

REFERENCES

Alam, M. M., Siwar, C., Murad, M. W., & Toriman, M. E. (2011). Farm level assessment of climate change, agriculture and food security issues in Malaysia. *World Applied SciencesJournal*, *14*(3), 431-442.

Baharudin, M. S. M., Ibrahim, R., Abdan, K., & Rashidi, A. (2018). Feasibility Of Green Commercial Vertical System For Climbing Food Plant In Urban Area. Inter*national Journal on Sustainable Tropical Design Research and Practice*. 11(2), 12-16.

Balafoutis, A. T., Evert, F. K. V., & Fountas, S. (2020). Smart Farming Technology Trends: Economic and Environmental Effects, Labor Impact, and Adoption Readiness. *Agronomy*, 10(5), 743.

Basso, D., Patuzzi, F., Castello, D., Baratieri, M., Rada, E. C., Weiss-Hortala, E., & Fiori, L. (2016). Agro-industrial waste to solid biofuel through hydrothermal carbonisation. *Waste management*, *47*, 114-121.

Beza, E., Reidsma, P., Poortvliet, P. M., Belay, M. M., Bijen, B. S., & Kooistra, L. (2018). Exploring farmers' intentions to adopt mobile Short Message Service (SMS) for citizen science in agriculture. *Computers and Electronics in Agriculture*, *151*, 295-310.

CEMA. (2017). Smart Agriculture for All Farms. Available at:

http://old.cema-agri.org/sites/default/files/publications/CEMA%20smart%20agriculture%20for%20all %20farms_December%202017_.pdf.

Chao, C. M. (2019). Factors determining the behavioural intention to use mobile learning: An application and extension of the UTAUT model. *Frontiers in psychology*, *10*, 1652.

Chappell, M. J., & LaValle, L. A. (2011). Food security and biodiversity: can we have both? An agroecological analysis. Agriculture and human values, 28(1), 3-26.

Chuah, Y. D., Lee, J. V., Tan, S. S., & Ng, C. K. (2019, June). Implementation of smart monitoring system in vertical farming. In IOP Conference Series: Earth and Environmental Science (Vol. 268, No. 1, p. 012083). IOP Publishing.

Das V, J., Sharma, S., & Kaushik, A. (2019). Views of Irish farmers on smart farming technologies: An observational study. *AgriEngineering*, 1(2), 164-187.

Das, P. (2015). Problems of rural farmer: a case study based on the lowphulabori village underthe raha block development area of Nagaon district, Assam. *IOSR J Humanit Soc Sci*, *20*,40-43.

Department of Statistics Malaysia. (2019). Selected Agricultural Indicators, Malaysia, 2019. Agriculture.

DOSM. (2020). Selected Agricultural Indicators. Available at: https://www.dosm.gov.my/v1/index.php?r=column/cthemeByCat&cat=72&bul_id=RX VKUVJ5TitHM0cwYWxlOHcxU3dKdz09&menu_id=Z0VTZGU1UHBUT1VJMFlpaXRRR0xpdz09

Duang-Ek-Anong, S., Pibulcharoensit, S., & Phongsatha, T. (2019). Technology Readiness forInternet of Things (IoT) Adoption in Smart Farming in Thailand. *Int. J. Simul. Syst. Sci.Technol*, *20*, 1-6.

Engotoit, B., Kituyi, G. M., & Moya, M. B. (2016). Influence of performance expectancy on commercial farmers' intention to use mobile-based communication technologies for agricultural market information dissemination in Uganda. *Journal of Systems and Information Technology*.

Far, S. T., & Rezaei-Moghaddam, K. (2017). Determinants of Iranian agricultural consultants'intentions toward precision agriculture: Integrating innovativeness to the technology acceptance model. *Journal of the Saudi Society of Agricultural Sciences*, *16*(3), 280-286.

Fornell, C., & Bookstein, F. L. (1982). Two structural equation models: LISREL and PLS applied to consumer exit-voice theory. *Journal of Marketing research*, *19*(4), 440-452.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal ofMarketing theory and Practice*, *19*(2), 139-152.

Husin, M. H., Loghmani, N., & Abidin, S. S. Z. (2017). Increasing e-government adoption in Malaysia: MyEG case study. *Journal of Systems and Information Technology*.

Ibrahim, A. R., Ibrahim, N. H. N., Harun, A. N., Kassim, M. R. M., Kamaruddin, S. E., & Witjaksono, G. (2018, July). Bird Counting and Climate Monitoring using LoRaWAN in Swiftlet Farming for IR4. 0 Applications. In *2018 2nd International Conference on Smart Sensors and Application (ICSSA)* (pp. 33-37). IEEE.

Jaabi, S. A., & Esemu, T. (2017). Fish enterprise financing and its impact on exports and research and development: The case of Uganda's fish industry. *Institutions and Economies*, 35-59.

Jong, D., & Wang, T. S. (2009). Student acceptance of web-based learning system. In *Proceedings. The 2009 International Symposium on Web Information Systems and Applications (WISA 2009)* (p. 533). Academy Publisher.

Junadi, J., & Sfenrianto, S. (2015). The analysis of consumer's intention model for using E- payment system in Indonesia. In *2015 International Conference on Sustainable Information Engineering and Technology (SIET)* (pp. 78-82). IEEE.

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and psychological measurement*, *30*(3), 607-610.

Lakhal, S., Khechine, H., & Pascot, D. (2013). Student behavioural intentions to use desktop video conferencing in a distance course: integration of autonomy to the UTAUT model. *Journal of Computing in Higher Education*, *25*(2), 93-121.

Leavy, J., & Hossain, N. (2014). Who wants to farm? Youth aspirations, opportunities and rising food prices. *IDS Working Papers*, *2014*(439), 1-44.

Lee, J. D., & Heo, C. M. (2020). The Effect of Technology Acceptance Factors on BehaviouralIntention for Agricultural Drone Service by Mediating Effect of Perceived Benefits. *Journal of Digital Convergence*, *18*(8), 151-167.

Li, W., Clark, B., Taylor, J. A., Kendall, H., Jones, G., Li, Z., ... & Frewer, L. J. (2020). A hybrid modelling approach to understanding adoption of precision agriculture technologies in Chinese cropping systems. *Computers and Electronics in Agriculture*, *172*, 105305.

Lim, L. J., Sambas, H., Goh, N. C., Kawada, T., & JosephNg, P. S. (2017). ScareDuino: Smart- Farming with IoT. *International Journal of Scientific Engineering and Technology*, 6(6),207-210.

Lu, Y., Papagiannidis, S., & Alamanos, E. (2019). Exploring the emotional antecedents and outcomes of technology acceptance. *Computers in Human Behaviour*, *90*, 153-169.

Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the Internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. *International journal of information management*, *34*(1), 1-13.

Masters, W. A., Djurfeldt, A. A., De Haan, C., Hazell, P., Jayne, T., Jirström, M., & Reardon, T. (2013). Urbanisation and farm size in Asia and Africa: Implications for food security and agricultural research. Global Food Security, 2(3), 156-165.

Michels, M., Fecke, W., Feil, J. H., Musshoff, O., Pigisch, J., & Krone, S. (2020).

Smartphoneadoption and use in agriculture: empirical evidence from Germany. *Precision Agriculture*, *21*(2), 403-425.

Mohamad, E., Abd Rahman, M. S., Rahman, A. A., Mohamad, N., Azlan, N. N., & Saptari, A. (2021). Investigation of The Awareness Level in Malaysia's Manufacturing Industries on the Implementation of Industry 4.0. *Journal of Industrial Engineering*, *6*(1), 53-66.

Mohamad, S. A., & Kassim, S. (2019, January). Examining the relationship between UTAUT construct, technology awareness, financial cost and e-payment adoption among microfinance clients in Malaysia. In *1st Aceh Global Conference (AGC 2018)* (pp. 351-357). Atlantis Press.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information systems research*, *2*(3), 192-222.

Murad, W., Molla, R. I., Mokhtar, M. B., & Raquib, A. (2010). Climate change and agricultural growth: an examination of the link in Malaysia. *International Journal of Climate Change Strategies and Management*.

Noordin, K. A. (2018). Agriculture: Addressing food security in Malaysia. *The Edge Malaysia*.

OECD. (2018). OECD Public Governance Reviews OECD Integrity Review of Thailand:Towards Coherent and Effective Integrity Policies. OECD.

Othman, Z. (2012). Information and communication technology innovation as a tool forpromoting sustainable agriculture: a case study of paddy farming in west Malaysia (Doctoral dissertation, University of Malaya).

Palau-Saumell, R., Forgas-Coll, S., Sánchez-García, J., & Robres, E. (2019). User acceptance of mobile apps for restaurants: An expanded and extended UTAUT-2. *Sustainability*, *11*(4), 1210.

Park, J., Yang, S., & Lehto, X. (2007). Adoption of mobile technologies for Chinese consumers. *Journal of electronic commerce research*, *8*(3), 196.

Patil, P., Tamilmani, K., Rana, N. P., & Raghavan, V. (2020). Understanding consumer adoption of mobile payment in India: Extending Meta-UTAUT model with personal innovativeness, anxiety, trust, and grievance redressal. *International Journal ofInformation Management*, *54*, 102144.

Pawlak, K., & Kołodziejczak, M. (2020). The role of agriculture in ensuring food security in developing countries: Considerations in the context of the problem of sustainable food production. *Sustainability*, *12*(13), 5488.

Pivoto, D., Waquil, P. D., Talamini, E., Finocchio, C. P. S., Dalla Corte, V. F., & de Vargas Mores, G. (2018). Scientific development of smart farming technologies and their application in Brazil. *Information processing in agriculture*, *5*(1), 21-32.

Ploetz, R. C. (2007). Diseases of tropical perennial crops: challenging problems in diverse environments. *Plant Disease*, *91*(6), 644-663.

Putri, D. A. (2018, May). Analysing factors influencing continuance intention of e-payment adoption using modified UTAUT 2 model. In *2018 6th International*

Conference on Information and Communication Technology (ICoICT) (pp. 167-173). IEEE.

Rahi, S., Ghani, M., & Ngah, A. (2018). A structural equation model for evaluating user's intention to adopt internet banking and intention to recommend technology. *Accounting*, *4*(4), 139-152.

Rahman, S. M. E., Islam, M. A., Rahman, M. M., & Oh, D. H. (2008). Effect of cattle slurry on growth, biomass yield and chemical composition of maise fodder. *Asian-AustralasianJournal of Animal Sciences*, *21*(11), 1592-1598.

Rasheed, A., & Mahmood, B. (2018). Modern Farming and Cooperation: A Sociological Analysis of Farming Families in Rural Punjab, Pakistan.

Rockström, J., Williams, J., Daily, G., Noble, A., Matthews, N., Gordon, L., ... & Smith, J. (2017). Sustainable intensification of agriculture for human prosperity and global sustainability. *Ambio*, *46*(1), 4-17.

Ronaghi, M. H., & Forouharfar, A. (2020). A contextualised study of the usage of the Internetof things (IoTs) in smart farming in a typical Middle Eastern country within the contextof Unified Theory of Acceptance and Use of Technology model (UTAUT). *Technologyin Society*, *63*, 101415.

Salloum, S. A., & Al-Emran, M. (2018). Factors affecting the adoption of E-payment systemsby university students: Extending the TAM with trust. *International Journal of Electronic Business*, *14*(4), 371-390.

Say, S. M. et al. (2018). 'Adoption of Precision Agriculture Technologies in Developed and Developing Countries', *The Online Journal of Science and Technology*, 8(1), p. 7. Available at: http://tojsat.net/journals/tojsat/volumes/tojsat-volume08-i01.pdf#page=16.

SCOPE. (2019). *Sarawak Digital Economy Strategy 2018 – 2022*.

Sharma, M., Joshi, S., Kannan, D., Govindan, K., Singh, R., & Purohit, H. C. (2020). Internetof Things (IoT) adoption barriers of smart cities' waste management: An Indian context. *Journal of Cleaner Production*, *270*, 122047.

Steele, D. (2017). Analysis of precision agriculture adoption & barriers in western Canada. *Final Report*.

Teschner, N. A., Orenstein, D. E., Shapira, I., & Keasar, T. (2017). Socio-ecological research and the transition toward sustainable agriculture. *International Journal of Agricultural Sustainability*, *15*(2), 99-101.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilisation. *MIS quarterly*, 125-143.

UN. (2015). SDGs: Sustainable Development Knowledge Platform. [online] Available at: https://sustainabledevelopment.un.org/sdgs.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178.

Zhang, A., Jakku, E., Llewellyn, R., & Baker, E. I. (2018). Surveying the needs and drivers fordigital agriculture in Australia. *Farm Policy Journal*, 15(1), 25-39.

Zhou, T. (2012). Examining location-based services usage from the perspectives of unified theory of acceptance and use of technology and privacy risk. *Journal of Electronic Commerce Research*, *13*(2), 135.

Zhou, T., Lu, Y., & Wang, B. (2010). Integrating TTF and UTAUT to explain mobile bankinguser adoption. *Computers in human behaviour*, *26*(4), 760-767.