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FACTORS INFLUENCING FARMER ADOPTION OF CLIMATE-SMART AGRICULTURE TECHNOLOGIES: EVIDENCE FROM MALAYSIA

Mohd Amar Aziz
Faculty of Administrative Science and Policy Studies
Universiti Teknologi MARA Pahang
Malaysia

Noor Hadzlida Ayob
Faculty of Human Sciences
Universiti Pendidikan Sultan Idris
Malaysia

Nor Azira Ayob
Faculty of Administrative Science and Policy Studies
Universiti Teknologi MARA Negeri Sembilan
Malaysia

Yarina Ahmad
Institute for Biodiversity and Sustainable Development
Universiti Teknologi MARA Shah Alam
Malaysia

Kamaruddin Abdulsomad
School of Economics and Management
Department of Economic History
Lund University
Sweden

Abstract: *As technology advances, people become increasingly dependent on technological tools to increase their work efficiency and productivity. Farming methods in the agriculture sector are also undergoing a shift from conventional to technology-driven modern agriculture practices, primarily because of their benefits and potential to mitigate the effects of climate change. However, the adoption rate of climate-smart agriculture technologies (CSAT) is considered to be very slow. Thus, this study was conducted to examine the factors that lead farmers to adopt CSAT in their agricultural practices. A sample of 185 farmers was used to investigate the main influencing factors in four contexts. The developed model was analyzed using the partial least squares structural equation modeling method. The results of this study suggest that institutions play a critical role as a contextual factor that leads individuals and societies to engage with CSAT, builds confidence, and convinces farmers to adopt these technologies.*

Keywords: *climate smart agriculture technologies, institutions, environment, sustainability*

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INTRODUCTION

Given the current environmental crisis, climate-smart agriculture technologies (CSAT) are widely advocated as a means of ensuring the sustainability of food production. Despite serious global concerns about environmental issues and climate change, scaling up CSAT practices seems to be a challenge, especially in developing countries (Mazhar et al., 2021). Numerous forms and categories of CSAT exist, encompassing a wide array of technologies relevant to various aspects of farming. These include techniques for technical and practical agriculture, water and soil management, livestock care, as well as an assortment of technological tools and digital solutions, extending to renewable energy and emission reduction strategies. Within each of these categories, a diverse range of technological methods is available for implementation. Examples include diversified and rotational cropping systems, drip irrigation and rainwater harvesting systems, organic farming practices, the use of GPS, drones, and IoT sensors, agroforestry, and integration of solar and wind energy systems in agriculture. Farmers can adopt any of these methods as part of their efforts to mitigate climate change.

However, CSAT adoption is also associated with several risks and uncertainties, as well as potential financial costs that may influence farmers' decisions. Several factors, including institutional structure (Fusco et al., 2020; Mazhar et al., 2021; Totin, et al., 2018), farmer skill levels (Anuga et al., 2019; Lee, 2017; Morgan et al., 2018), increasing workload (Andrieu et al., 2017; Tsige, Synnevåg, & Aune, 2020), need for new skills (Raj & Garlapati, 2020; Shahbaz, 2022), lack of awareness, lack of information, lack of experience (Mashi, Inkami, & Oghenejabor, 2022; Nyasimi et al, 2017; Ouédraogo et al., 2019), and perceptions of new technologies (Khoza et al., 2021; Ouédraogo et al., 2019; Senyolo et al., 2018) are considered barriers to farmer adoption and use of CSAT.

According to Raile et al. (2021) and Makate (2019), when attempting to encourage the adoption of CSAT, it is also important to consider factors that create or discourage incentives. Incentives, such as financial and non-financial benefits, can encourage farmers to adopt new technologies, while disincentives, such as the cost of a new technology, can discourage farmers from adopting it. Financial disincentives often arise when new technologies require expensive investments, such as the purchase of land or equipment, which may not be feasible for smallholder farmers (Autio, Johansson, Motaroki, Minoia, & Pellikka, 2021). Non-financial disincentives may also arise if the CSAT is not compatible with traditional farming practices, which may result in lower yields and higher input costs. For example, a CSAT that requires specialized equipment or different crop varieties may not be compatible with smallholders' existing farming practices (Akouwerabou, Zanré, Savadogo, & Kaboré, 2022). To counter this, information from farmers to technology providers is crucial to ensure that their products are more compatible with traditional farming practices. This can only be done through a concerted effort by many, including the government, to assist farmers adopt CSAT. It is important to encourage farmers to adopt CSAT because this agricultural innovation can help farmers with food security, climate change adaptation, and mitigation (Meshesha, Birhanu, & Ayele, 2022).

The literature also suggests that governments can provide financial and technical support to farmers, while non-governmental organizations can disseminate information about the benefits of CSAT and provide training to farmers (Dey & Mishra, 2022; Waaswa, Nkurumwa, Kibe, & Kipkemoi, 2022). Strategies include expanding the commercialization of the technology (Casey, Bisaro, Valverde, Martinez, & Rokitzki 2021). If the technology is not effectively commercialized, farmers may not even know it exists. In addition, trialability is one of the strategies that can be used to promote CSAT to farmers (Kabir et al., 2022). This will enable farmers to have a first-hand experience with the technology, which can help reduce some of their risk aversion. Farmer motivation is also an important factor influencing CSAT adoption. Farmers may be motivated to adopt CSAT if the technology is easy to use and the benefits are apparent (Antwi-Agyei et al., 2021). In addition, farmers are more likely to adopt CSAT if they see their peers using the technology (Khoza et al, 2021; Totin et al, 2018). This demonstrates that institutional, individual, and social context influences farmers' use of CSAT.

Although previous studies have explained the numerous factors that lead to the adoption of CSAT, there is a dearth of research that comprehensively frames the relationship between these aspects and the institutional, individual, and societal context. It is essential to examine the factors from a contextual perspective to determine which elements require attention and improvement to promote CSAT adoption among farmers. This is because many farmers are affected by climate change, resulting in disappointing agricultural outcomes. In 2021, Malaysian agriculture contributed 7.1 percent to the country's gross domestic product (GDP), with this figure declining slightly by 0.3 percent from the previous year (Statista Search Department, 2022). The country has experienced more extreme weather conditions, including more floods and landslides. Unpredictable weather and climate conditions, as well as a lack of technological solutions to support farmers, could affect agricultural production (Rahman, 2009). The initial strategy, which uses CSAT, is therefore considered suitable to solve the crisis. With this in mind, it is expected that this study will help policymakers determine which areas need to be emphasized and formulate ideas based on the data obtained to encourage farmers to adopt the technologies.

THE THEORETICAL UNDERPINNINGS

This study integrates several important theories that serve as the basis for analyzing the factors that influence farmers' adoption of CSAT in different contexts. The three integrated theories are the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology Acceptance Model (TAM), and the Diffusion of Innovation (DOI) theory. The factors for CSAT adoption are explained with reference to the three theories above, based on institutional, individual, and societal contexts, respectively.

The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh, Bala, and Davis in 2003. This theory attempts to explain how individuals and groups adopt and use technology. Four constructs serve as the basis for the theory: performance expectancy, effort expectancy, social influence, and facilitating conditions. This theory states that individuals and groups adopt and use technology to fulfill their performance and effort expectations. In addition, social influence and facilitating conditions play a role in an individual's decision to use or not use technology.

Venkatesh, Thong, and Xu (2012) extended the UTAUT model by adding hedonic motivation, price value, and habit as additional factors that influence a person's decision to adopt and use technology. Hedonic motivation is the extent to which a person derives pleasure from using technology. Price value is the degree to which a person believes the technology is worth the price they pay, and habit is a person's tendency to use technology out of habit rather than due to external factors (Venkatesh et al., 2012). However, in this study, two variables, hedonic motivation and habit, were omitted.

This is because climate-smart agriculture is not a fancy new technological device or tool for self-improvement, but rather a concern related to aspects of more effective agricultural management. Farmers are more interested in the benefits they derive from using technology. They will not use technology just for hedonistic purposes. They are primarily motivated by economic factors, such as increasing their productivity, reducing costs, and maximizing profits. If a technology does not offer economic benefits or does not align with farmers' financial goals, they are less likely to adopt it, even if it offers hedonistic benefits (Akouwerabou et al., 2022; Autio et al., 2021). For this reason, hedonic motivation and habit are not considered in the model, resulting in a more parsimonious model.

The Technology Acceptance Model (TAM)

The technology acceptance model (TAM) is a theoretical model used to explain and predict user acceptance of technology. The technology acceptance model consists of four main components: perceived ease of use, perceived usefulness, attitude toward use, and behavioral intention to use. Recently, UTAUT has replaced TAM in many usage-based research studies. Perceived usefulness and perceived ease of use can be related to effort and performance expectancies respectively and are two of the similar constructs (Dwivedi, Mustafee, Carter, & Williams, 2010; Sair & Danish, 2018).

Although perceived ease of use is considered very similar and comparable to effort expectancy, perceived usefulness is also considered similar to performance expectancy. However, in this research, the terminology of perceived ease of use and perceived usefulness preferred by TAM was used. It is assumed that the items for both constructs are closer to the individual perspective of technology adoption. Therefore, this study uses the terms 'perceived ease of use' and 'perceived usefulness' to measure an individual's role in technology use.

The Diffusion of Innovation (DOI)

The theory of diffusion of innovations (DOI) assumes that innovations are not static but are constantly evolving and growing over time. Specifically, innovations are most likely to be adopted by members of the same social group or class who are already using similar technologies. For an innovation to spread beyond its original group, it must first be accepted and adopted by the group that was originally most likely to adopt it. Relative advantage, compatibility, complexity, observability, and trialability are considered the five constructs underlying DOI theory (Scott et al., 2008).

However, various constructs were released to develop a model congruent with institutional, individual, and social contexts so that parsimony could be achieved. According to Alkhwaldi and Kamala (2017), a well-established and comprehensive theoretical model should consider parsimony in terms of simplifying the model with the fewest constructs and maximum predictive potential. Therefore, this study uses only the construct of trialability to integrate the model, which is included in an institutional framework for DOI. The relationship between constructs based on institutional, individual, and social contexts in technology adoption is explained in the next section, which also develops a study model.

RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

This study examines the institutional, individual, social, and environmental contexts that are hypothesized to be the most influential factors in CSAT adoption. These four contexts are derived from the previously discussed theories UTAUT, TAM, and DOI, and the constructs of the theory are assigned according to the suitability of the context.

Institutional Context

Several theoretical constructs can be considered as part of the institutional context. Commercialization is one of the antecedent constructs that does not appear in the theory discussed, but is considered appropriate to be placed in an institutional context. The commercialization of a technology can influence its perceived usefulness and ease of use. Kim, Park, Sawng, and Park (2019) discovered a gap in the process of technology commercialization that can be addressed by capturing the notion of technology value for productization. Productization here refers to the process of transforming a service or idea into a marketable product that can be sold to customers. The problem with this, however, is that technological services or ideas developed by developers to be marketed are not perceived as useful by users. This shows that there is a disparity between what technology developers consider valuable and what consumers actually value. Therefore, efforts to commercialize the technology more broadly are critical to improving users' perceptions of its importance (Chiesa & Frattini, 2011).

In addition to commercialization, product trialability is considered one of the factors that must be taken into account in an institutional context to ensure that consumers believe that the technology is useful and easy to use (Lubensky & Schmidbauer, 2020). Zhu and Chang (2014) found that perceived usefulness and perceived ease of use of technology-based services are two of the most important determinants of trial adoption. Trialability facilitates users in gaining a pre-adoption experience with the technology before committing to its usage. The short trial period allows users to recognize the technology's benefits and ease of use of the technology, which influences their decision to adopt it. Karahoca, Karahoca, and Aksöz (2018) reported that trialability affects users' perceptions of the usability of the technology, and that this effect may vary by gender. This clearly shows that trialability is one of the factors that determine individuals' use of technologies. Consequently, this aspect becomes an intriguing area of study, particularly when exploring farmers' perspectives on utilizing CSAT. However, from an agricultural technology perspective, little attention has been paid to this issue.

To ensure that users find the CSAT they use as useful and easy to use, facilitating conditions must be present. According to a study by Chung, Han, and Joun (2015) technology readiness and facilitating condition influence perceived usefulness and perceived ease of use. In addition, Yaseen, Bryceson, and Mungai (2018) emphasized the importance of facilitating conditions within the context of support institutions that can effectively support and positively influence farmers' adoption of modern technologies. This role of facilitating conditions proves to be particularly beneficial for smallholder farmers, ensuring that they perceive agricultural processes involving technology to be more accessible and beneficial. Based on previous studies related to the institutional context in forming user views about the advantages of using technology, several hypotheses were established related to the adoption of CSAT.

H1 : Commercialization significantly affects perceived usefulness of CSAT
H2 : Commercialization significantly affects perceived ease of use of CSAT
H3 : Trialability significantly influences perceived usefulness of CSAT
H4 : Trialability significantly influences perceived ease of use of CSAT
H5 : Facilitating condition significantly affects perceived usefulness of CSAT
H6 : Facilitating condition significantly affects perceived ease of use of CSAT

Individual Context

The initial hypotheses explain how the institutional context influences individuals' use of technology. This section then explores how the individual context influences the social context. Individual factors are measured by three variables: perceived usefulness, perceived ease of use and price value. Numerous studies show that social influence can affect individuals' adoption of technologies (AlSaleh & Thakur, 2019; Graf-Vlachy, Buhtz, & König, 2018; Wu & Chen, 2017). This study, however, focuses on how individual context affects social influence. Risselada, de Vries, and Verstappen (2018) found that individual assessments of the benefits of using technology and the convenience of technology on social media can influence more people to adopt technology. This indicates that individual reviews highlighting the benefits of the technology can trigger a social influence, leading to the expression of positive sentiments about the technology within the broader social community.

In addition, individuals with different orientations reacted differently to the selling price under the influence of varying amounts of information. Asymmetric information, for example, when the seller or product provider knows more about the benefits of the product, leads the seller or product provider to believe that the technology product is sold at a reasonable price, while the buyer believes that the technology product is overpriced and not worth buying (Lin, Lin, & Hung, 2008). Thus, if the consumer sees the benefits of the product, they will believe that the price offered represents value. However, the high price is unaffordable for smallholder farmers. Therefore, a competitive price or subsidy for CSAT is required to encourage farmers to utilize innovation (Long, Blok, & Poldner, 2017). Based on these explanations, several hypotheses were developed that link individual context to social influence have been developed.

H7 : Perceived usefulness significantly affects social influence about CSAT
H8 : Perceived ease of use significantly affects social influence about CSAT
H9 : Price value significantly affects social influence about CSAT

Reviews of technology products by individuals not only influence the social community, but also prompt environmentally conscious users to opt for the technology. The benefits of adopting technology are also seen as having the potential to increase environmental awareness (Fernández, Camargo, & Nascimento, 2019). Initially using technology to make work easier and reap the benefits that come from the output will increase environmental awareness. This happens because the user perceives the changes caused by the use and the price value of the technology (An, Di, Yao, & Jin, 2022). This will further motivate farmers to adopt CSAT. Therefore, based on the discussion of the factors in the individual context, three hypotheses are proposed.

H10 : Perceived usefulness significantly influences adoption of CSAT
H11 : Perceived ease of use significantly influences adoption of CSAT
H12 : Price value significantly influences adoption of CSAT

Social Context

The importance of the social context in encouraging farmers' adoption of CSAT is widely recognized. Discussions on how social factors influence technological use are notably broad and multi-dimensional. From the viewpoint of the UTAUT, social influence is understood as the extent to which significant others (like family, friends, or colleagues) shape an individual’s attitude towards embracing technology. Social influence is observed to increase technology usage and contribute to its growth (Venkatesh et al., 2012). This concept aligns with earlier perspectives from Bijker, Hughes, and Pinch (1987), who elucidated the development of technology, asserting that its trajectory is not solely determined by technical advancement but is also shaped by social factors. This is because technological evolution is an open-ended process, wherein various social groups have the opportunity to influence the design and functionality of technology to better meet societal needs.

Oudshoorn and Pinch (2005) further elaborate on the evolution of technology by focusing on the user dimension, highlighting how users not only shape technology but are also shaped by it in return. This concept is pivotal as it illustrates that the advent of specific technologies establishes new norms and cultures within social interactions. Supporting this notion, Korjonen-Kuusipuro et al. (2017), state that culture emerges from the interplay of behavioral practices and norms, which are both reflected in and influenced by daily life and user needs for technological solutions. The progression of such technologies is integral to fostering connections among individuals, communities, and society at large. In today's expanding digital realm, technology has birthed new cultural phenomena, particularly visible through social media and community reviews of technological products. These interactions transcend traditional cultural boundaries of ethnicity and geography, creating communities that converge to discuss and evaluate technologies relevant to them. This dynamic has given rise to a novel culture of interaction within specific social media communities, as identified by Benami and Carter (2021), forming what might be termed 'homogeneous zones' in these digital spaces.

Research by Risselada et al. (2018) indicates that individual evaluations and feedback on technology products, shared either on online purchasing sites or community forums, can significantly sway others’ decisions to adopt or discard a technology. Ocker (2010) notes that while positive, critical, and constructive comments can foster creativity, negative feedback may stifle it, engendering feelings of disappointment and disillusionment towards the technology. This dynamic of user feedback, ingrained in the culture of social media technology, reiterates the concept that technological product development is influenced by social creativity in seeking optimal solutions, as described by Bijker et al. (1987) and Oudshoorn and Pinch (2005). In the realm of CSAT, studies by Azadi et al. (2021) and Bazzana, Foltz, and Zhang (2022) reveal that social exchanges among farmers, particularly those revolving around the advantages of climate-smart systems and practices, significantly bolster CSAT usage. This dynamic is recognized as an integral element of interaction within the agricultural community. In this context, social influence is shaped by perceptions gleaned from community reviews and evaluations, particularly regarding a technology's practicality, ease of use and value for money. These aspects are deemed pivotal within the community, leading to a more widespread adoption of the technology. In light of this social context, the following hypotheses are proposed for exploration:

H13 : Social influence significantly affects CSAT adoption.

Environmental Context

The last aspect considered important is the awareness of farmers to protect the environment and ensure the sustainability of food security in the country by adopting CSAT. Numerous research findings suggest that CSAT adoption can have an impact on food security sustainability (Azadi et al., 2021; Bazzana et al., 2022; Hasan et al., 2018; Wekesa, Ayuyu, & Lagat, 2018). This is due to the fact that the use of CSAT effectively addresses climate change, enhances efficiency and productivity, and mitigates climate change-related challenges in agriculture. Simultaneously, this leads to an upsurge in agricultural production and contributes to the sustainability of food security. This demonstrates that raising awareness of CSAT is critical to ensuring environmental sustainability. The use of CSAT motivated is not only by the desire for profit or agricultural benefits, but also by an awareness of environmental protection that simultaneously increases the productivity of food production in the country. Therefore, a hypothesis is proposed.

H14 : CSAT adoption affects sustainable food security.

From the discussion of previous studies and the formulation of research hypotheses. Then a testable research model was developed. The study model depicted in Figure 1 is based on theories and contexts that include institutions, individuals, social, and the environment.

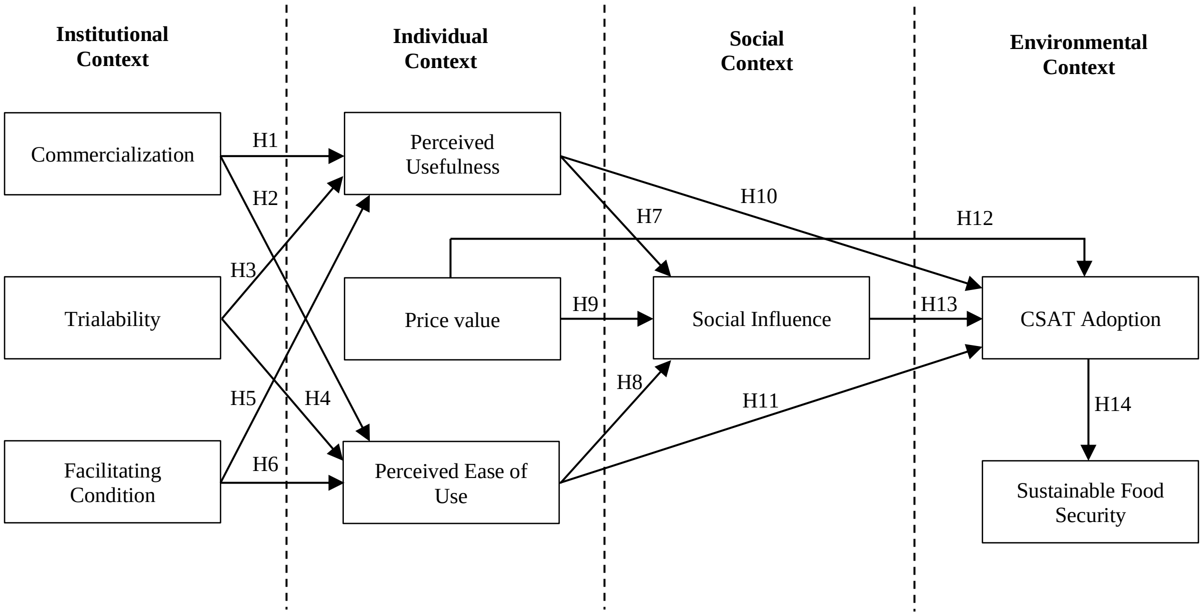

Figure 1. Research Model

METHODOLOGY

Research Design and Sample

This study employed a quantitative approach to collect data regarding the adoption of CSAT by farmers. The choice of a quantitative approach in this study stems from a positivist perspective, prioritizing objectivity in examining the causal relationships anticipated within the contexts of CSAT adoption. Data were collected from respondents using a cross-sectional design. A cross-sectional survey was chosen due to numerous factors noted by Spector (2019), including (1) the exploratory nature of the study, (2) not knowing the exact time frame, and (3) investigating the natural consequences for farmers. Since this study seemed to meet all three criteria, a cross-sectional research design was appropriate. The study sample consisted of farmers from Perlis, Kedah, and Perak states in northern Peninsular Malaysia. The sample size for the study was calculated using the G*Power application (Faul et al., 2007). Using a medium effect size of 0.15, an alpha level of 0.5, and a statistical power of 0.95, the minimum sample size required was 160. Data were collected from respondents using a questionnaire in the form of a booklet and an online survey (via a Google form) using stratified random sampling. After screening the data, 185 samples were found to be suitable for analysis. This number exceeded the minimum sample size required and was considered sufficient.

Instruments

A questionnaire was distributed to the respondents and used as a research instrument to measure each variable of the study model. The questionnaire consisted of five sections with fifty-four measurement items. The five sections included the respondent's profile (8 items), measurements for institutional context (12 items), individual context (16 items), social context (5 items), and environmental context (13 items).

The institutional context included three variables: commercialization, trialability and facilitating condition. The instrument for commercialization was adapted from Chiesa and Frattini (2011), for trialability from Fu et al. (2007), and facilitating condition from Wut, Lee and Xu (2022). For the individual context, it included three measurable variables: perceived usefulness, perceived ease of use and price value. The measures of perceived usefulness and perceived ease of use were adapted from Davis (1989) and Wang, Lew, Lau, and Leow (2019), while the price value was adapted from Venkatesh et al. (2012). Social context has only one variable, social influence, and the measures were adapted from Venkatesh et al. (2012) and Madigan et al. (2016). The last part is the environmental context, which has two variables: CSAT adoption and sustainable food security. The items on CSAT adoption were adapted from Sain et al. (2017) and Neufeldt et al. (2015), while sustainable food security was adapted from Azadi et al. (2021) and Bazzana et al. (2022).

As for the measurement scale, each item was measured using a five-point scale. The coding employed incorporates features of equidistance and also describes symmetry, making the five-point scale appropriate for multivariate analysis (Hair, Hult, Ringle, & Sarstedt, 2017). Considering the criteria, this study used the following coding categories: (1) strongly disagree, (2) disagree, (3) neither agree nor disagree, (4) agree, and (5) strongly agree. To ensure that the coding was symmetrical, the third scale was set to neutral, which is 'neither agree nor disagree', and the distance between each scale was considered equal to ensure that equidistance is attained.

Data Analysis

Partial Least Square Structural Equation Modeling (PLS-SEM) was chosen as the method of analysis for this study. SmartPLS, version 3.3.2, was used to assess the data for the analysis. This method was chosen for several reasons: (1) it is an exploratory study; (2) the goal is to predict the key factors that encourage farmers to adopt CSAT; and (3) a complex structural model is used to conduct the analysis (Hair et al., 2017). Based on these considerations, PLS-SEM is considered an appropriate method for data analysis. There are two stages for the analysis procedure: (1) the assessment of the measurement model and (2) the assessment of the structural model. After the first stage (measurement model) established the validity and reliability of the model, the assessment moved to the second stage (structural model) to test the hypotheses. The analytical report was prepared in accordance with the recommendations of Hair, Rusher, Sarstedt, and Ringle (2019) to ensure that the reporting of results was systematic, robust and comprehensive.

RESULT

Respondent Profiles

Of the total 185 responses, 124 (67%) were males and the remaining 61 (33%) were females. The age of the respondents ranged from 21 to 53 years, with the age distribution as follows: 42 respondents aged 21 to 30 years (22.7%), 81 respondents aged 31 to 40 years (43.8%) and 62 respondents aged 41 and above (33.5%). The largest proportion of respondents were Malay (87.5%), followed by Chinese (7.6%), other races (3.8%) and Indians (1.1%). In terms of agricultural experience, 44.3 percent had less than 5 years of experience, 36.8 percent had more than 5 to 10 years of experience and 18.9 percent had more than 10 years of experience. In terms of agricultural land area, 41.6 percent of the farmers have less than one acre, 24.9 percent have between one and five acres, 22.1 percent have between six and ten acres, and 11.4 per cent have more than ten acres. The landholdings of the respondents in this study closely align with the average size possessed by most Malaysian farmers, typically ranging from 2 to 3 hectares (equivalent to 4,942 to 7,413 acres). Additionally, both the median and mean figures for the respondents' land areas indicate that the farms of those participating in the study are generally around 5 acres in size. This profile indicates that not all respondents were smallholder farmers; there were also farmers with medium and large land sizes. Therefore, a wide range of farmers were represented in this analysis in terms of their perspectives on the adoption of CSAT.

Assessment of Measurement Model

In the measurement model assessment stage, the built model is assessed to ensure that it is valid and has good reliability before hypothesis testing is carried out. Four aspects are evaluated in this stage: indicator reliability, internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2017). For the evaluation of indicator reliability, the factor loading values for each construct are assessed. The factor loading threshold with a value greater than 0.708 is considered to have good indicator reliability (Hair et al., 2019). Three indicators, T1, FC2 and PV1, which had factor loading values below 0.708 during this evaluation process were omitted from the model. As shown in Table 1, the remaining indicators have factor loading values ranging from 0.729 to 0.943, indicating that the reliability of the indicators for a given construct is good.

Next, the internal consistency reliability was assessed using composite reliability and Cronbach's alpha. Both composite reliability and Cronbach's alpha have the same threshold values. For exploratory research, values between 0.60 and 0.70 are considered 'acceptable,' while values between 0.70 and 0.90 are considered 'satisfactory to good' (Hair et al., 2019). However, concerns arise when reliability values exceed 0.95, indicating potential issues with response patterns and redundant items within the construct. The results, as shown in Table 1, indicate that the composite reliability values range from 0.912 to 0.947, while Cronbach's alpha ranges from 0.877 to 0.936. These findings demonstrate that the constructed model exhibits good internal consistency reliability.

Table 1. Construct validity and reliability

Construct	Indicator	Loadings	Composite Reliability	Cronbach's Alpha	AVE
Commercialization	C1	0.901	0.915	0.877	0.730
	C2	0.834			
	C3	0.871			
	C4	0.808			
Trialability	T2	0.890	0.945	0.912	0.851
	T3	0.943			
	T4	0.935			
Facilitating Conditions	FC1	0.902	0.935	0.896	0.826
	FC3	0.942			
	FC4	0.894			
Perceived Usefulness	PU1	0.898	0.931	0.907	0.730
	PU2	0.907			
	PU3	0.783			
	PU4	0.905			
	PU5	0.768			
Perceived Ease of Use	PE1	0.800	0.946	0.929	0.778
	PE2	0.907			
	PE3	0.906			
	PE4	0.875			
	PE5	0.917			
Price Value	PV2	0.729	0.912	0.884	0.675
	PV3	0.807			
	PV4	0.853			
	PV5	0.834			
	PV6	0.876			
Social Influence	SI1	0.741	0.915	0.883	0.684
	SI2	0.822			
	SI3	0.863			
	SI4	0.829			
	SI5	0.872			
CSAT Adoption	CSAT1	0.783	0.947	0.936	0.691
	CSAT2	0.848			
	CSAT3	0.778			
	CSAT4	0.773			
	CSAT5	0.836			
	CSAT6	0.895			
	CSAT7	0.901			
	CSAT8	0.824			
Sustainable Food Security	SFS1	0.902	0.940	0.923	0.760
	SFS2	0.922			
	SFS3	0.889			
	SFS4	0.739			
	SFS5	0.895			

Convergent validity was assessed using the average variance extracted (AVE) as the metric. An AVE threshold of 0.50 or higher indicates that the construct captures at least 50% of the variance of its items (Hair et al., 2019). The analysis reveals that all constructs possess an AVE value exceeding 0.50, ranging from 0.675 to 0.851. This underscores the constructs' strong convergent validity, indicating that over half of the item variance can be accounted for within each construct.

Next, discriminant validity was assessed to determine the extent to which each construct in the model differed empirically from the others. According to Henseler, Ringle, and Sarstedt (2015), the heterotrait-monotrait (HTMT) ratio of correlations offers a more robust measure of discriminant validity compared to the traditional Fornell-Larcker criterion. This is especially important when indicator loadings on the construct exhibit only slight differences. Consequently, the HTMT was employed in this study to evaluate discriminant validity. In the proposed HTMT analysis, a value of 0.90 or higher indicates a lack of discriminant validity. As shown in Table 2, the HTMT values for all constructs ranged from 0.363 to 0.854, indicating that the constructed model indeed demonstrated discriminant validity. Thus, based on the measurement model analysis, it can be concluded that the constructed model achieved an acceptable level of validity and reliability.

Table 2. Discriminant validity using HTMT ratio

	C	T	FC	PU	PE	PV	SI	CSAT	SFS
Commercialization									
Trialability	0.548								
Facilitating Conditions	0.603	0.436							
Perceived Usefulness	0.608	0.802	0.450						
Perceived Ease of Use	0.560	0.423	0.522	0.669					
Price Value	0.574	0.512	0.471	0.645	0.738				
Social Influence	0.680	0.783	0.525	0.854	0.566	0.544			
CSAT Adoption	0.427	0.421	0.363	0.606	0.605	0.613	0.666		
Sustainable Food Security	0.433	0.457	0.453	0.600	0.542	0.620	0.617	0.671	

Assessment of Structural Model

Once it was confirmed that the constructed model had achieved a satisfactory level of validity and reliability in the assessment of the measurement model, the evaluation shifted to the structural model. During this stage, various aspects were examined. Prior to testing the significance and relevance of the relationships within the structural model through hypothesis testing, it was essential to ensure the absence of collinearity issues within the model. To address the collinearity concern, the variance inflation factor (VIF) was calculated and analyzed within the structural model. A VIF value below 5.0 is typically considered indicative of a lack of collinearity issues (Hair et al., 2019). Based on the obtained results, the VIF values for the constructs within the model ranged from 1.00 to 3.198. These findings affirm that the constructed model did not exhibit critical collinearity issues.

Table 3. Structural relationship and hypotheses results

Hypo.	Path	Coeff.	f^2	*p*-values	95% Conf. Int.	Supported?
H1	C → PU	0.233	0.083	0.010**	[0.054, 0.420]	Yes
H2	C → PE	0.319	0.097	0.001**	[0.146, 0.517]	Yes
H3	T → PU	0.599	0.640	0.000***	[0.439, 0.775]	Yes
H4	T → PE	0.163	0.030	0.026*	[0.029, 0.312]	Yes
H5	FC → PU	0.053	0.005	0.524	[-0.119, 0.209]	No
H6	FC → PE	0.237	0.058	0.009**	[0.046, 0.399]	Yes
H7	PU → SI	0.745	0.801	0.000***	[0.579, 0.893]	Yes
H8	PE → SI	0.040	0.000	0.723	[-0.141, 0.276]	No
H9	PV → SI	0.028	0.001	0.755	[-0.156, 0.186]	No
H10	PU → CSAT	0.041	0.005	0.942	[-0.319, 0.327]	No
H11	PE → CSAT	0.355	0.115	0.026*	[0.155, 0.585]	Yes
H12	PV → CSAT	0.204	0.041	0.080	[-0.036, 0.430]	No
H13	SI → CSAT	0.395	0.142	0.008**	[0.099, 0.668]	Yes
H14	CSA → SFS	0.676	0.841	0.000***	[0.550, 0.817]	Yes

Note(s): *$p < 0.05$, **$p < 0.01$, and ***$p < 0.001$

Hypothesis tests were subsequently conducted to ascertain the significance and relevance of the relationships within the structural model. The estimation of path coefficients representing the hypothesized relationships between the constructs utilized 5,000 bootstrap samples. Out of the fourteen hypotheses tested, nine exhibited statistically significant results, while five yielded non-significant outcomes. Within the institutional context, all hypotheses yielded significant results, except for the facilitating condition hypothesis concerning perceived usefulness ($\beta = 0.053$, $p > 0.05$). Consequently, H5 was rejected. However, both commercialization's impact on perceived usefulness ($\beta = 0.233$, $p < 0.01$) and perceived ease of use ($\beta = 0.319$, $p < 0.01$) were statistically significant, supporting hypotheses H1 and H2, respectively. Furthermore, the effects of trialability on perceived usefulness ($\beta = 0.599$, $p < 0.001$) and perceived ease of use ($\beta = 0.163$, $p < 0.05$) were also significant, thereby confirming hypotheses H3 and H4. In contrast, the effect of the facilitating condition was only significant for perceived ease of use (β = 0.237, p < 0.01), providing support for hypothesis H6.

Within the individual context, three factors were measured: price value, perceived usefulness, and perceived ease of use. However, the results revealed that neither price value (β = 0.028, p > 0.05) nor perceived ease of use (β = 0.040, p > 0.05) exerted a significant effect on the social influence driving farmers' adoption of CSAT. Consequently, hypotheses H8 and H9 were rejected. On the other hand, perceived usefulness was found to have a significant impact on social influence (β = 0.745, p < 0.001), supporting hypothesis H7. From the perspective of the individual context on CSAT adoption, only perceived ease of use yielded a significant result (β = 0.355, p < 0.05), thus supporting H11. However, perceived usefulness and price value yielded insignificant results (β = 0.041, p > 0.05) and (β = 0.204, p > 0.05), respectively, leading to the rejection of hypotheses H10 and H12. Within the social context, the factor of social influence demonstrated a significant impact on CSAT adoption (β = 0.395, p < 0.01), supporting H13. This indirectly suggests that perceived usefulness, mediated through social influence, has an indirect effect on CSAT adoption (β = 0.288, p < 0.05), illustrating the role of social influence as a mediator in informing farmers about the benefits of CSAT. In the environmental context, farmers' perspective unquestionably revealed a significant impact of CSAT adoption on the sustainability of food security (β = 0.676, p < 0.001), thus supporting H14.

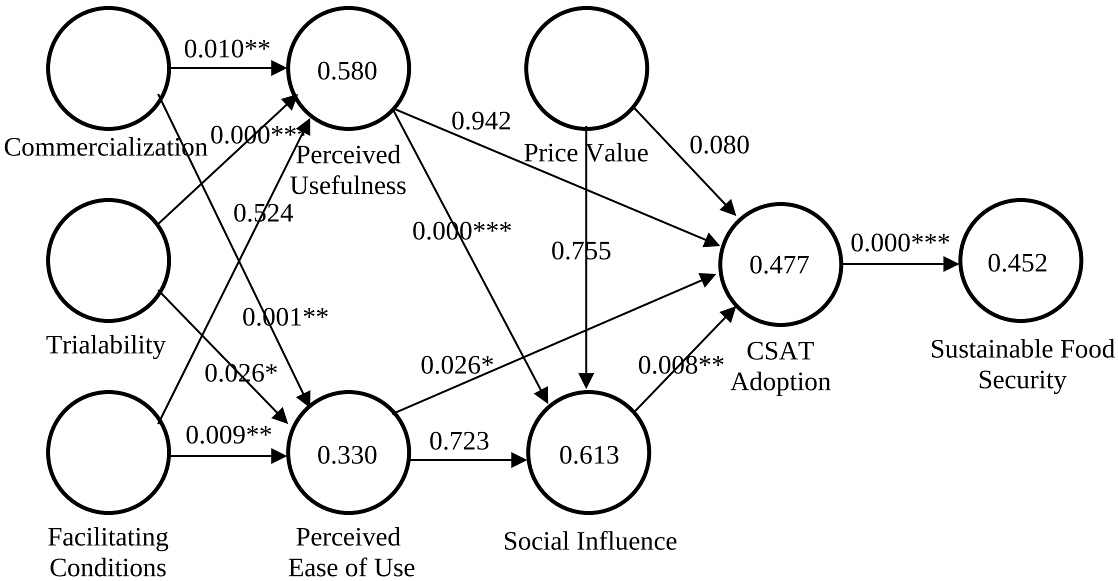

Figure 2. Result of PLS analysis

Following the hypothesis testing, the coefficient of determination (R^2) value was computed to determine the extent of variance explained by each endogenous construct. In this study, five endogenous constructs were examined, and as suggested by Hair et al. (2019), R^2

values of 0.75, 0.50, and 0.25 correspond to substantial, moderate, and weak explanatory power, respectively. The findings of the analysis revealed that two endogenous constructs exhibited moderate predictive power, with R^2 values falling within the range of 0.50 to 0.74. Meanwhile, three endogenous constructs displayed weak predictive power, with R^2 values ranging from 0.25 to 0.49. Specifically, the endogenous construct with the highest R^2 value was social influence ($R^2 = 0.613$), followed by perceived usefulness ($R^2 = 0.580$), CSAT adoption ($R^2 = 0.477$), sustainable food security ($R^2 = 0.452$), and perceived ease of use ($R^2 = 0.330$).

This study further assessed the effect size (f^2) of the exogenous constructs, which contributes to the predictive power of the endogenous construct R^2. As a general guideline, effect sizes greater than 0.02, 0.15, and 0.35 indicate small, medium, and large f^2 values, respectively (Hair et al., 2019). The findings of the study indicate that three constructs, namely trialability → perceived usefulness ($f^2 = 0.640$), perceived usefulness → social influence ($f^2 = 0.801$), and CSAT adoption → sustainable food security ($f^2 = 0.841$), exhibited substantial effect sizes (f^2). These constructs significantly contributed to the variance change and predictive power of the endogenous construct R^2. Table 3 provides an overview of the effect sizes of other exogenous constructs, which were found to have only a small effect size.

Furthermore, the predictive accuracy of the PLS path model was assessed using Stone-Geisser's Q^2, which measures the predictive relevance. Based on the blindfolding results with an omission distance of seven, all endogenous constructs exhibited Q^2 values greater than zero. As per the guideline, Q^2 values above 0, 0.25, and 0.50 indicate small, medium, and large predictive relevance of the PLS path model, respectively (Hair et al., 2019). In this study, all endogenous constructs demonstrated medium predictive relevance, with Q^2 values ranging from 0.255 to 0.419. These findings confirm that the developed model possesses medium predictive relevance. The final step in evaluating the structural model involved assessing its out-of-sample predictive power using $PLS_{predict}$ (Shmueli et al., 2019). Through a 10-fold cross-validation, all $Q^2_{predict}$ values were found to be greater than zero, indicating that the model outperformed the naïve benchmark. By comparing the PLS-RMSE and LM-RMSE indicators, it was observed that only a minority of PLS-RMSE values resulted in higher prediction errors than LM-RMSE, indicating that the model exhibited medium predictive power.

DISCUSSIONS

Based on the results of the study, the model developed has medium predictive power in determining the factors that drive farmers to adopt CSAT. Since this is an exploratory study on the causal-predictive relationship in a complex model, medium predictive power is considered good in explaining the factors for adoption of CSAT among farmers. In terms of institutional context, the study found that the role of institutions is important in informing farmers about the benefits and advantages of adopting CSAT in their agricultural production. This finding is consistent with previous research by Mazhar et al. (2021), Fusco et al. (2020), and Totin et al. (2018), who found that the role of institutions is an important factor in CSAT adoption.

However, this research goes beyond the conventional understanding of institutions and explores their nuanced capabilities, particularly in fostering commercialization. This is substantiated by the significant relationship observed between the commercialization factor and farmers' perception of the usefulness of CSAT, as well as the technology's ability to enhance task performance. Therefore, it is imperative to further expand and develop the aspect of commercialization to enhance farmers' awareness of the available technologies that can enhance agricultural productivity and provide them with benefits. As highlighted by Kim et al. (2019), addressing the information asymmetry between developers and customers regarding the perceived value of a technology through commercialization is a key factor in promoting the technology's recognition for its functional benefits.

Furthermore, the trialability factor holds significant importance in instilling farmers' confidence in the benefits of technology and providing them with firsthand experience of how it can simplify their tasks and work processes. This significance becomes evident as the results indicate a substantial relationship between trialability and both perceived usefulness and perceived ease of use. The substantial effect size of trialability on perceived usefulness further emphasizes the critical role of this factor in building confidence in the benefits of CSAT. This argument finds support in previous research, which has demonstrated that when consumers have the opportunity to try a product, their confidence in its quality increases, regardless of whether it aligns precisely with their perceived value (Kim et al., 2019). Additionally, a trial version has the potential to reshape the user's mindset and enhance their intention to further explore the features and benefits of the technology product (Chiesa & Frattini, 2011).

Regarding the facilitating condition, it is evident that it does not directly influence perceived usefulness but solely impacts perceived ease of use. This is because the purpose of the facilitating condition is to provide support, education, and assistance to users in utilizing the technology more effectively, without necessarily making them explicitly aware of the benefits. If users perceive a particular technology as challenging to use and require facilitating conditions, they are likely to perceive it as less useful. This finding aligns with the research conducted by Chung et al. (2015), which emphasized the significance of facilitating conditions in relation to perceived ease of use rather than perceived usefulness. Hence, it becomes apparent that facilitating conditions have a greater impact on perceived ease of use compared to perceived usefulness.

In the individual context, it was observed that perceived usefulness had a significant impact on social influence, whereas price value and perceived ease of use did not exhibit significance in relation to social influence. This can be attributed to the fact that farmers prioritize the benefits and advantages offered by technology in enhancing their agricultural productivity. The substantial gains in productivity resulting from these technology benefits contribute to an increase in their social influence. These findings are consistent with the research conducted by Risselada et al. (2018), who identified that when social media users review a product's benefits, it enhances social influence towards using the product. Hence, the results of this study indicate that CSAT operates in a similar manner, with its benefits exerting a comparable effect on social influence.

On the contrary, ease of use is not the primary influencing factor for farmers when it comes to exerting influence on society. This can be attributed to their familiarity with traditional production methods (Akouwerabou et al., 2022). However, an interesting finding emerged that perceived ease of use does impact CSAT adoption. It is understandable that farmers are more likely to adopt technology as a CSAT if it is user-friendly. Nevertheless, ease of use does not significantly influence the social impact of agriculture, marking a notable distinction in this regard. In comparison to other studies, such as the research conducted by Risselada et al. (2018), user reviews on ease of use do not appear to exert a significant influence on the adoption of CSAT. Similarly, price value does not affect social influence in agriculture or CSA practices. This can be attributed to the presence of information asymmetries associated with CSA technology. Farmers evaluate the value of CSA technology and practices differently, depending on their perception of price value as being valuable or not, as highlighted by Kim et al. (2019). This difference can potentially stem from the heterogeneity between small and large farmers, although it was not observed within the scope of this study.

In the social context, social influence acts as a mediator between perceived usefulness and CSAT adoption. This finding is intriguing as it suggests that while farmers acknowledge the benefits of CSAT, their adoption of it is generally influenced by the social community. In contrast, if the technology is perceived as ease of use, farmers are more likely to continue utilizing it. However, to strengthen CSAT adoption, social influence must serve as a facilitator in promoting the benefits. This result aligns with the studies conducted by Azadi et al. (2021) and Bazzana et al. (2022), which highlight the influential role of the social community among farmers in adopting CSAT. In this context, the institutional framework plays a crucial role by enhancing opportunities for testing CSAT and facilitating their commercialization, enabling farmers to maximize the benefits and broaden their sphere of influence. Regarding the environmental context, CSAT undeniably contribute to achieving sustainable food security, as supported by the significant results and substantial effect sizes observed between CSAT adoption and food security sustainability (Bazzana et al., 2022; Hasan et al., 2018; Wekesa et al., 2018). These findings indicate that farmers recognize the potential of CSAT in increasing productivity and promoting the sustainability of food security.

While this study has delineated the effects of institutional, individual, social, and environmental contexts on the adoption of CSAT and sustainable food security, its findings are confined to farmers in Malaysia. Consequently, it is plausible that variations in geographical factors, national economic policies, and diverse cultural practices might yield differing outcomes. Therefore, in advancing understanding and awareness about CSAT adoption and climate-change responsiveness, this study puts forth several recommendations for future research. One such recommendation is to conduct comparative analyses across different societal segments, such as varied ethnic groups, which may possess distinct cultures and operational methods. Future research could also concentrate on small-scale farmers, who are often perceived as less capable of implementing CSAT. Additionally, these findings could be expanded to explore the roles of government entities, private sector organizations, and NGOs in promoting CSAT. This exploration might include examining perspectives related to incentives, subsidies, and up-skilling programs tailored for CSAT usage among farmers.

CONCLUSIONS

This study has highlighted the significant role of institutions in influencing user perceptions, particularly in relation to commercialization and trialability. Commercialization serves as a crucial avenue for educating farmers about the benefits associated with technology, thereby informing them of the available technologies capable of enhancing productivity. To enhance farmers' confidence in the benefits of technology, it is imperative for them to gain hands-on experience with it. Therefore, farmers should be provided with opportunities to engage with state-of-the-art agricultural technology, allowing them to experiment and explore its potential. The benefits arising from such experimentation will not only impact the agricultural community but also drive the adoption of CSAT among farmers, ultimately contributing to the sustainability of food security.

Furthermore, the individual context plays a crucial role in ensuring that farmers perceive CSA technology as useful and ease of use. This emphasizes the importance of the initial processes of commercialization and trialability, which help address information asymmetry regarding the value, benefits, and features of CSAT. The benefits derived from these processes can be further disseminated to exert social influence within the community, thereby promoting the adoption of CSAT among farmers. Therefore, to effectively accomplish this objective, it is crucial to foster synergies among the government, private sector, and non-governmental organizations (NGOs) in establishing an efficient institutional structure that supports and promotes CSAT within the agricultural sector.

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All correspondence should be addressed to
Noor Hadzlida Ayob
Faculty of Human Sciences
Universiti Pendidikan Sultan Idris
35900 Tanjong Malim, Perak, Malaysia
hadzlida@fsk.upsi.edu.my

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