



Faculty of Economics and Business

**Factor Influencing the Adoption of Smart Farming Technology: The
Role of Technology Awareness as Moderator**

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Doctor of Business Administration

2024

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A dissertation submitted

In fulfillment of the requirements for the degree of Doctor of Business Administration

Faculty of Economics and Business
UNIVERSITI MALAYSIA SARAWAK
2024

DECLARATION

I declare that the work in this dissertation was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The dissertation has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



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Date : 7 July 2024

ACKNOWLEDGEMENT

I am indebted to Almighty Allah for the sanctification and guidance in providing me with this challenging journey in my dissertation process. There are many people who support and encourage me, and they have made my DBA journey easy and fun.

I would like to express my special gratitude to my supervisor Assoc. Prof. Dr Hamrila binti Abdul Latif, thank you for her guidance, support, and valuable feedback throughout my dissertation process journey. Her insightful comments and suggestions have significantly contributed to the quality of my study.

I would like to extend my sincere gratitude to my Faculty Dean, Prof. Dr Rossazana binti Ab Rahim for her support and concern throughout my dissertation process from day one till its completion.

Furthermore, I would like to express my appreciation to my family and friends, especially my husband, Mohd Shafarin bin Shafie, who has provided me with constant encouragement and backing during this journey.

In addition, I would like to extend my sincere gratefulness to all my colleagues at the Department of Agriculture, Kuching District for their assistance during data collection process. Thank you to Mr. Philip Kapia, Mdm. Norsiha, Mr. Walter Unggok, Mr. Raymond, Miss Krenchsa Stella, Miss Liaw Chuen Hui, Mdm. Diana, Mdm. Suraya, Mdm. Subaikah, Mdm. Emelda and Mdm. Dayang Meriah.

Finally, I would like to acknowledge the support of the Faculty of Economics and Business, Universiti Malaysia Sarawak, for providing me with the necessary resources and facilities to carry out this research.

ABSTRACT

The adoption of Smart Farming Technologies (SFT) is essential for improving food security, especially for farmers. Challenges such as population growth, geopolitical tensions, low productivity and lack of knowledge hinder the widespread use of SFT, particularly in regions like Sarawak. This study identifies the factors influencing farmers' acceptance to adopt SFT, using the Unified Theory of Acceptance and Use of Technology (UTAUT) framework with technology awareness as a moderator. Through a quantitative survey of 330 farmers in various regions of Sarawak, key determinants like performance expectancy, effort expectancy, social influence, facilitating conditions, and technology awareness were identified. Data analysis using PLS-SEM revealed that while farmers are inclined to adopt SFT, significant barriers remain, particularly related to performance expectancy and social influence. The findings suggest that addressing these barriers can help the Sarawak government and stakeholders develop suitable technologies and policies to enhance food security. Ultimately, this could lead Sarawak to achieve sustainable food security and become a net food exporter by 2030, contributing to economic development.

Keywords: Smart Farming Technologies, Technology Acceptance, Food Security, Technology Awareness, UTAUT

***Faktor yang Mempengaruhi Penggunaan Teknologi Pertanian Pintar: Peranan
Kesedaran Teknologi sebagai Moderator***

ABSTRAK

Penggunaan Teknologi Pertanian Pintar (TPP) adalah penting untuk meningkatkan keterjaminan makanan, terutamanya bagi petani. Cabaran seperti pertumbuhan penduduk, ketegangan geopolitik, pengeluaran yang rendah dan kekurangan pengetahuan menghalang penggunaan meluas TPP, terutamanya di kawasan seperti Sarawak. Kajian ini mengenal pasti faktor-faktor yang mempengaruhi penerimaan petani untuk penggunaan TPP, menggunakan kerangka Teori Penerimaan Penggunaan Teknologi Bersatu (TPPTB) dengan kesedaran teknologi sebagai moderator. Melalui tinjauan kuantitatif ke atas 330 petani di pelbagai kawasan di Sarawak, penentu utama seperti jangkaan prestasi, jangkaan usaha, pengaruh sosial, keadaan memudahkan, dan kesedaran teknologi telah dikenalpasti. Analisis data menggunakan PLS-SEM mendedahkan bahawa walaupun petani cenderung untuk penggunaan TPP, halangan yang ketara masih ada, terutamanya berkaitan dengan jangkaan prestasi dan pengaruh sosial. Penemuan ini mencadangkan bahawa menangani halangan ini boleh membantu kerajaan Sarawak dan pihak berkepentingan membangunkan teknologi dan polisi yang sesuai untuk meningkatkan keterjaminan makanan. Akhirnya, ini dapat membawa Sarawak mencapai keterjaminan makanan yang lestari dan menjadi pengeksport makanan bersih menjelang tahun 2030, menyumbang kepada pembangunan ekonomi.

Kata kunci: *Teknologi Pertanian Pintar, Keterjaminan Makanan, Penerimaan Teknologi, Kesedaran Teknologi, TPPTB*

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LIST OF ABBREVIATIONS

AC	The Acceptance of Farmers to Adopt SFT
AI	Artificial Intelligent
AM	Additive Manufacturing
AR	Augmented Reality
ARS	Simulation, Autonomous Robotic Systems
AVE	Average Variance Extracted
AW	Technology Awareness
BDA	Big Data Analysis
BRT	Behavioural Reasoning Theory
CB-SEM	Covariance Based Structural Equation Modelling
CC	Cloud Computing
CMV	Common Method Variance
CPS	Cyber-Physical Systems
CR	Composite Reliability
CSA	Climate Smart Agriculture
DOI	Diffusion of Innovation Theory
DT	Digital Twin
DTPB	Decomposed Theory of Planned Behaviour
EE	Effort Expectancy
EFA	Exploratory Factor Analysis
FAO	Food and Agriculture Organization
FC	Facilitating Conditions

FS	Food Security
GDP	Gross Domestic Product
GFSI	Global Food Security Index
HTMT	Heterotrait-Monotrait Ratio
IoT	Internet of Things
IDR	Import Dependence Ratio
IDT	Innovation Diffusion Theory
M-Ficord	Ministry of Food, Commodity and Regional Development Sarawak
MM	Motivational Model
NFI	Normed Fit Index
PE	Performance Expectancy
PFT	Precision Farming Technologies
PLS-SEM	Partial Least Square Approach to Structural Equation Modelling
SCT	Social Cognitive Theory
SDGs	Sustainable Development Goals
SEM	Structural Equation Modelling
SF	Smart Farming
SFT	Smart Farming Technologies
SI	Social Influence
SP	Smart Product
SMS	Short Message Service
SPSS	Statistical Package for Social Science

SRMR	Standardised Root Mean Square Residual
TAM2	Technology Acceptance Model 2
TOE	Theory of Expanded
TRA	Theory of Reasoned Action
TPB	Theory of Planned Behaviour
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
WSN	Wireless Sensor Networks

CHAPTER 1

INTRODUCTION

1.1 Introduction

Food is a vital component for human survival. Every nation must have enough quantity and quality food sources for the growing population. In an extended period, prompt population growth coupled with a lack of food may result in famine and starvation, contributing to a rise in mortality. In concordance with global famines and food crises, food security was initiated at the 1974 World Food Conference. The academic community and politics have evolved, developed, and diversified this concept. Subsequently, several definitions of food security have been devised in light of the original perspective on food security issues. Scholars and international organisations may have defined it differently, but the core concept remained unchanged.

In addition, food security is a matter of utmost importance since it plays a pivotal role in safeguarding the overall welfare of its people. Ensuring that every individual has equitable and uninterrupted access to an adequate supply of safe and nutritious food to fulfil their dietary requirements is essential. The agriculture industry plays a crucial part in its food supply. For instance, climatic diversity and good soil facilitate the development of a wide range of crops, including rice, fruits, and vegetables. This is aligned with the Sustainable Development Goals (SDGs) that aim to reduce hunger, attain food security, promote nutritious food, and establish sustainable agricultural practices, as outlined in SDG 2.

Meanwhile, farmers, technology providers, legislators, and experts in agricultural innovations are currently elevating agricultural automation to a higher level. Various hi-tech apparatuses and methodologies introduced in the agricultural sector are commonly identified

as Smart Farming Technologies (SFT); they offer beneficial outcomes regarding cost-saving and growth in productivity and earnings (Basso et al., 2016; Virk et al., 2020).

1.2 Background of the Study

Food security is commonly defined as the equitable and consistent provision of nutritious, safe, and adequate food that satisfies the dietary requirements and preferences of all individuals, ensuring their ability to lead an active and healthy life (FAO, 2006). This definition is rooted in the World Food Summit of 1996. Furthermore, one of the United Nations' Sustainable Development Goals (SDGs) emphasised ending hunger, achieving food security, and improving nutrition by 2030. According to the Ministry of Agriculture and Food Security (2023), Malaysia's performance in Global Food Security Index (GFSI) is ranked 41st, which is a decrease of seven places and moderately performed compared to the previous year, is ranked 39th, up nine places performed well with a score of 70.1. There is a decrease of 1.6 for the overall score faced by Malaysia, which consists of affordability, availability, quality and safety, and sustainability and adaptation, compared to the previous year's score of 5.1, which is the highest increase in score among the 113 countries involved.

A high self-sufficiency ratio (SSR) indicates an adequate food supply inside a country, representing one of the dimensions of food security. Availability encompasses several factors, such as domestic production, imports, exports, and the quantity of existing stockpiles inside the country. When the Self-Sufficiency Ratio (SSR) exceeds 100.0 percent, it signifies that the supply or production of a particular agricultural commodity is adequate to meet the nation's demands. Conversely, if the SSR falls below 100.0 percent, it shows an insufficiency in meeting the country's requirements. According to the Department of Statistics Malaysia (2023), several vegetables and fruits fall below 100 percent SSR, such

as round cabbage (45.6 percent), mango (32 percent), chilli (29.7 percent), and ginger (15.9 percent).

Although Malaysia has its agricultural output, it remains reliant on imports from other nations for some commodities. The Department of Statistics Malaysia (2023) reported that the value of imported food products has increased to RM75.6 billion in 2023 from RM44.6 billion in 2022. As a result of a more significant surge in imports relative to exports, the trade deficit for food products has grown to RM31.0 billion, representing a 24.3 per cent increase over the preceding year. For instance, the Import Dependence Ratio (IDR) for the following items surpassed 50.0 percent in 2022: ginger (2022: 85.6 percent; 86.5 percent in 2021); mango (2022: 79.7 percent; 92.6 percent in 2021); chilli (2022: 74.0 percent; 75.1 percent in 2021); and round cabbage (2022: 55.5 percent; 61.3 percent in 2021). Concurrently, the nation is compelled to continue importing agricultural products such as apples, shallots, onions, and garlic due to climate inconsistencies.

Due to its continued reliance on imports to maintain its food supply, Sarawak will continue to be susceptible to food insecurity for the foreseeable future. In 2022, food imports through Sarawak amounted to RM5.6 billion. The current surge in food prices can be attributed to any disruption in the import supply chain from exporting nations. The underdevelopment of the agro-food sector's capacity is an ongoing concern regarding Sarawak's food security. In recent years, commodity crops, particularly oil palm, have dominated agricultural development over sustenance crops.

Based on Figure 1.1, the increasing number of populations in Sarawak also impacts the higher food demand. According to the Department of Statistics Malaysia (2023a), the estimated population of Malaysia in the fourth quarter of 2022 is 33 million, up 1.30 percent from the fourth quarter of 2021 (32.6 million). In addition, Sarawak is estimated to see a

population growth from 2.45 million in 2020 to 2.47 million in 2021(Economic Planning Unit Sarawak, 2022). The projection shows that the population in Malaysia is increasing, which can influence the country's food demand. By 2050, it is estimated that the demand for food security will increase by 70 to 100 percent due to projected population growth (Silva, 2018). In order to sustain Malaysia's economic growth and meet the requirements of millions of starving people, food security is becoming increasingly important (Husni, 2017). Figure 1.1 illustrates the population trend from 2017 to 2021 in Sarawak.

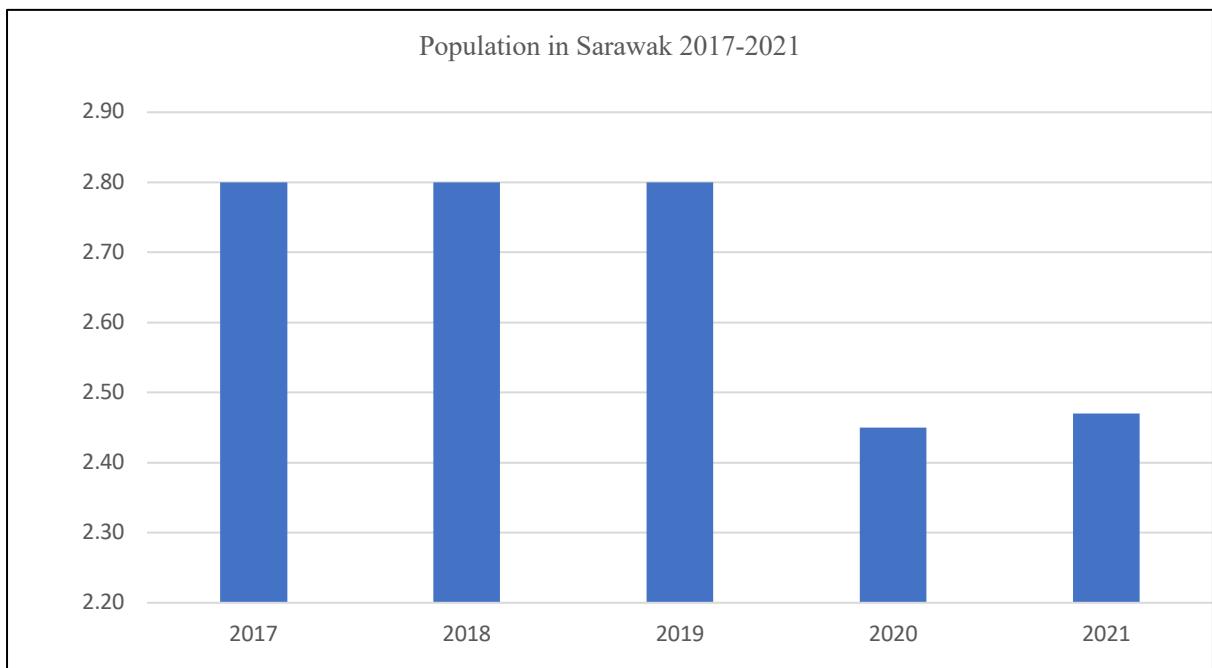


Figure 1. 1: Population in Sarawak 2017-2021
Source: Economic Planning Unit Sarawak (2022)

In order to maintain food security in the region, introducing SFT to farmers can offer plenty of benefits. Integrating advanced sensors, robotics, artificial intelligence, and other digital technologies into agriculture is called smart agricultural technologies. These technologies provide numerous advantages, such as optimising water and fertiliser use, decreasing labour costs, increasing crop production, and minimising environmental impact.

However, farmers need to implement intelligent farming technologies in their agricultural endeavours, as this can help to increase productivity and income. In addition, it can also reduce overall spending time and improve the quality of agricultural products, ultimately contributing to the maintenance of food security in terms of availability, accessibility, utilisation, and stability.

Moreover, the state government has enacted to urge the farmers to adopt and practice the digitalisation of agricultural technologies as they offer various benefits. Based on the Sarawak Digital Economy Strategy (SDES) 2018 – 2022, the government's goals are to increase the agriculture sector's productivity and efficacy and gain access to new markets for agricultural products (State Service Modernisation Unit, 2017). According to Sarawak Digital Economy Strategy 2018 – 2022, there are three prominent initiatives by the government to achieve goals, as mentioned before. Firstly, adopt digital technologies to transform the agricultural sector and drive innovation. For instance, the implementation of IoT and sensors for smart farming, the implementation of a geospatial system for agriculture planning and operation support in the development of agro parks, and the development of anchor farmers. Secondly, establish an efficient distribution system for agriculture inputs and products, such as the IoT for collection, processing, and packaging centres, collection centres, intelligent supply chains, and logistics. Lastly, develop new markets and expand existing ones for agricultural produce and products, collaborating with domestic and international investors and venture capitalists, branding, and e-commerce.

Therefore, a better understanding of the factors influencing the acceptance of SFT among farmers in Sarawak is a severe matter of endorsing SFT execution, thus ensuring a sustainable food production practice in the region. The report will also provide

recommendations regarding promotional ideas and support during the introduction of SFT practice and its maintenance in Sarawak.

1.3 Problem Statement

The surging growth in population, global climate change, and ever-changing lifestyles, such as the trends in consumption, impact the food security of a nation (Farooq et al., 2022). In addition, the geopolitical friction between Russia and Ukraine has significantly impacted the availability of raw materials for local producers as the price of fertilisers increases (Laborde & Mamun, 2022). This conflict inevitably leads to a plummet in agricultural production and economic activity.

The issue of food security is increasingly emerging as a prominent global topic, particularly in light of projections indicating that the global population is expected to reach 9.7 billion by the year 2050, equivalent to almost 20.6 percent of the present population (Department of Economic and Social Affairs, 2019). As a preparation to secure adequate food, the food production and supply should be at a minimum of 70 percent increment and double in the emerging countries, unlikely to be achieved via conventional means; therefore, automation in agriculture is a must by introducing new technologies in the sector (Husni, 2017; Beloev, 2021). The application of SFT is advantageous for farmers since it increases market competitiveness by producing high-quality commodities, reducing crop loss, lowering cost, and increasing revenue. In developing nations, SFT is preferred because they increases yield and allows for faster production than conventional methods (Schukat & Heisi, 2021; Pillai & Sivathanu, 2020; Wu, 2022).

Meanwhile, Dato Sri Dr Stephen Rundi Utom, the Minister of Modernization of Agriculture and Regional Development mentioned both its population and demand for food

sources are growing in Sarawak (Wong, 2022). It is an unresolved ongoing situation. Increasing population necessitates a proportional increase in food availability to ensure everyone's food security (Kaur, 2019). Datuk Patinggi Tan Sri Abang Johari Tun Openg, the Chief Minister of Sarawak, stated that the state government is actively pursuing the adoption of modern technology in the agro-based sector and along the agriculture supply chain in order to enhance the agriculture sector's competitiveness and sustainability (Ten, 2022). Regrettably, only a few farmers use SFT in their agricultural activities due to a lack of knowledge and skill in SFT and inadequate financial support to acquire technologies (M-FICORD, 2023). This is due to a need for more awareness that the farmers may need to learn the potential benefit of SFT due to adequate outreach programs and information dissemination initiatives.

Furthermore, Sarawak's current agricultural output is insufficient to support its role as a food exporter, despite the fact that it possesses the ability to export a diverse range of agricultural products (Pei Pei, 2018). The agriculture sector has significant challenges due to a scarcity of human labour, persistent reliance on conventional farming techniques, and the absence of efficient supply chain networks. The current state of the agriculture sector relies on traditional agricultural methods, which are not aligned with the principles of sustainable agriculture. As a result, low adoption of technology in agriculture can lead to low productivity and bring environmental damage, leading to a decline in agricultural output over time.

This low production capacity in essential food crops results in insufficient local food supply, compelling the region to rely heavily on imports to meet its dietary needs (Hanif, 2023). This dependency not only strains the local economy but also poses risks to food security, especially in the face of global supply chain disruptions. Addressing the factors that

limit the expansion of vegetable and fruit farming among Sarawak's farmers is crucial to reducing import dependency and ensuring a stable, self-sufficient food supply.

Despite the significant agricultural workforce in Sarawak, with 1,559,101 farmers reported by the Department of Agriculture Sarawak (2022), there is a notable underrepresentation in the production of vegetables and fruits. Only 76,732 farmers are engaged in cultivating these essential crops, according to the Department of Agriculture Malaysia (2022). This discrepancy highlights a critical issue in the agricultural sector of Sarawak, where the vast majority of farmers are not contributing to the production of vegetables and fruits. This situation poses a challenge to food security and economic diversification in the region. Addressing the barriers and challenges that prevent a larger portion of the farming population from engaging in vegetable and fruit production is imperative to enhancing the agricultural output and sustainability of Sarawak.

Rahman et al. (2008) and Tambi et al. (2021) showed the previous study on the 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, insufficient fertilisation, and poor practice of data management. Besides, the limited resources and lack of understanding of the smart farming technologies adoption and use also contribute to the country's economy being left behind compared to other countries (Coleman et al., 2016; Ghasemaghaei., 2019; O'Connor & Kelly., 2017; Nam et al., 2015). Ayim et al. (2022) and Barakabitze et al. (2017) highlight several significant barriers to the adoption of digital extension technologies by smallholder farmers, such as inadequate infrastructure, insufficient ICT knowledge, financial limitations, poor ICT policies, and inefficiencies in agricultural institutions. Besides, social, and cultural factors also can contribute to the low adoption of SFT (Wee, 2023). For instance, the attachment to and cultural significance of

traditional farming methods can deter farmers from adopting new technologies, as well as limited peer support and concerns about potential risks and consequences. These barriers collectively result in a low adoption rate of digital extension technologies among smallholder farmers, as observed by Coggins et al. (2022). According to Chatterjee (2018), the main challenges are the lack of awareness about the technologies among the farmers and the lack of usage of high levels of technology such as machinery.

The acceptance to adopt smart farming technologies is a complex process influenced by numerous factors that farmers weigh in their decision-making as entrepreneurs or stakeholders (Nakano et al., 2018). SFT represent innovations that require scholarly attention, focusing on their adoption based on the attributes of these innovations. So, it is important to know the acceptance of farmer to adopt SFT in order to sustain food security.

On another concern, there are only a few scholarly works available that explicitly discuss food security in Sarawak in detail (Abdullah et al., 2020); for example, discussion on food security during Covid-19 (Abdullah et al., 2020), the food security at Mak Yun village (Kaur et al., 2021), the food security and its tourism potentials (Hashim et al., 2019; Langgat et al., 2011), and the food safety and nutrition (Cooper, 2013; Rahman et al., 2012). Other food-related issues, such as hunting and foraging, are frequently mentioned briefly in studies on the economic conditions of Sarawak (Bennett, 2002; Onn, 2018). Therefore, it is necessary to examine the impact of the acceptance of farmers to adopt SFT to sustain food security in Sarawak.

The ultimate value of technological innovation is highly dependent on farmers' acceptance, which can contribute to the growth of agricultural productivity and efficiency. This study aims to identify the crucial factors influencing the acceptance of the farmers to adopt SFT in agriculture activities in order to sustain food security in Sarawak.

1.4 Research Gaps

Robinson et al. (2011) provided a definition of research gaps as those that have yet to be systematically identified. Robinson et al. (2011) devised a methodical structure for the identification of voids in the research literature. Furthermore, they emphasise that in order to facilitate researchers in their pursuit of undertaking pertinent future investigations, it is critical to furnish them with meticulously identified and characterised research spaces. The research gaps of this study are subsequently addressed.

1.4.1 Practical Gaps

The growth of technology adoption, namely emerging digital technologies, drives the implementation of new technologies in various sectors (Verhoef et al., 2021). The purpose of the adoption of technologies in the sector is to ensure benefits such as increased productivity and efficiency (Papagiannidis & Marikyan, 2020). There are a few researchers use the Unified Theory Acceptance and Use of Technology (UTAUT) to examine the adoption intentions of farmers for SFT, IoT, climate-smart agriculture (CSA), smart product and sustainable farming technology, and precision farming technologies (Wee & Lim, 2022; Pfeiffer et al., 2021). However, the adoption of SFT among farmers in Sarawak is still low (M-Ficord, 2023; Ullah et al., 2020a); a few of the reasons are due to a lack of exposure and low knowledge of advanced technologies related to agricultural activities. Prior literature on technology adoption has primarily concentrated on the adoption intention behaviour of farmers (Shcukat & Heisi, 2021; Ronaghi & Forouharfar, 2020).

Nevertheless, a limited number of studies mainly focus on the acceptance of farmers on the adoption of technologies. Most farmers need to become more familiar with smart agricultural technologies because they are uncommon and relatively new to the industry. Nonetheless, it significantly influences farmers and the sustenance of food security in

Sarawak. Therefore, it is essential to identify the main factor influencing the acceptance of farmers to adopt SFT in sustaining food security in Sarawak, as this can assist the policymakers, stakeholders, farmers, and researchers in developing proper actions to increase their awareness and identify the obstacles they face.

1.4.2 Theoretical Gaps

Theoretically, the Unified Theory of Acceptance and Use of Technology (UTAUT) has been utilised extensively in pertinent research. The moderators of UTAUT, such as age, working experience, and farm size, are identified to affect behavioural intention significantly. So, in order to measure the acceptance of the farmers to adopt SFT, this study adopts technology awareness as a moderator role. Technology awareness is rarely applied as a moderator in UTAUT, especially in the scholarly works related to agriculture activity. Furthermore, the existing studies review exposed that only a few studies are carried out on how to set awareness as a moderator within a construct (Daniali et al., 2022). In addition, farmers' awareness of technology is an essential indicator of their adoption of technology (Ullah et al., 2020). Technology awareness as a moderate construct has been examined in previous m-commerce studies (Abubakar & Ahmad, 2013; Omar, 2011) and behavioural intentions to use 4.5G mobile technologies (Daniali et al., 2021). The greater the attention, the greater the technology's diffusion, and vice versa. These investigations are undoubtedly valuable in learning about the adoption of SFT. In addition, this study attempts to fill the gaps by employing technology awareness as a moderator to explain farmers' acceptance to embrace SFT to sustain food security in Sarawak.

1.5 Research Questions

There are several questions regarding this study. The inquiries are enlisted as below:

- I. How does the performance expectancy affect the acceptance of farmers to adopt SFT?
- II. How does the effort expectancy affect on the acceptance of farmers to adopt SFT?
- III. How does the social influence affect on the acceptance of farmers to adopt SFT?
- IV. How does the facilitating conditions affect on the acceptance of farmers to adopt SFT?
- V. How does technology awareness moderate the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions and the acceptance of farmers to adopt SFT?
- VI. What is the impact on the acceptance of farmers to adopt SFT in sustaining food security?

1.6 Research Objectives

The general objective of this study is to identify the factors influencing the acceptance of the farmers to adopt SFT in sustaining food security in Sarawak. Specifically, the following are the aims of this investigation:

- I. To assess the effect of the performance expectancy on the acceptance of farmers to adopt SFT.
- II. To examine the effect of the effort expectancy on the acceptance of farmers to adopt SFT.

- III. To identify the effect of social influence on the acceptance of farmers to adopt SFT.
- IV. To determine the effect of facilitating conditions on the acceptance of farmers to adopt SFT.
- V. To test the effect of technology awareness moderate the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions and the acceptance of farmers to adopt SFT.
- VI. To investigate the impact of the acceptance of farmers to adopt SFT in sustaining food security.

1.7 Significance of the Study

Due to the rise in the population, there will be a corresponding rise in food demand. According to the State Service Modernisation Unit (2017), the adoption of digital technologies in transforming agricultural sectors and promoting innovation can increase agricultural sector productivity and efficiency. The practice of SFT has many potential benefits. It may assist farmers in optimising resource utilisation, reducing labour costs, and increasing crop yields, resulting in an overall improvement in terms of income and enhanced quality of life. The implementation of smart farming can reduce the risk of resource depletion, such as soil fertility, postharvest losses, and over-spending, associated with agricultural activities (Sissoko et al., 2023). In addition, the adoption of these technologies can promote sustainable food production practices, thereby contributing to the region's long-term food security. According to Schukat and Heisi (2021), SFT has the potential to assist farmers in producing in ways that are more resource-efficient, sustainable, and profitable

while also offering positive impacts on the environment and climate. So, this study aims to identify the factor influencing the farmers acceptance of SFT in sustaining food security.

1.7.1 Government and Policymakers

This study is expected to yield new insights into agricultural activities that may help boost agriculture's economic growth and productivity towards food security sustainability. This information can assist the government and policymakers in developing policies and strategies to promote the adoption of these technologies and ensure the region's agricultural practices are sustainable.

1.7.2 Farmers and Stakeholders

This study may provide a valuable understanding of the challenges that are present in the agricultural sector in Sarawak, specifically on the acceptance to adopt SFT. The findings and recommendations of this study may have practical implications for farmers and stakeholders in Sarawak. For instance, the farmers' awareness of SFT still needs to improve, which may contribute to their reluctance to adopt SFT (Sa'ari et al., 2018). It delivers potential benefits to farmers and stakeholders to develop decision-making, process, and control measures that can contribute to greater regional productivity and food security sustainability.

1.7.3 Researchers and Academics

This study can contribute to the limited literature on intelligent agricultural technologies in the context of Sarawak. Additionally, this study endeavours to lay out a fresh construct that explains the impact of SFT adoption on food security and serves as a reference to critical players in this field. UTAUT is widely used in relevant research, for instance, the study on the use of IoT in smart farming in the Middle East demonstrates a positive impact of performance expectancy, effort expectancy, social influence, individual factors, and

facilitation conditions on the intention to use IoT (Ronaghi & Forouharfar, 2020). The findings can contribute to a better understanding of factors that influence the acceptance of these technologies and explain how they can be promoted among Sarawak's farmers. This can be especially useful for researchers and academics interested in intelligent farming technologies and their potential influence on agriculture in developing regions.

In conclusion, the significance of the proposed study rests in its potential to contribute to the development of sustainable agricultural practices and guarantee food security in Sarawak. The findings may serve as valuable information to the government, policymakers, stakeholders, researchers, academics, and farmers in the region, providing a road map for promoting the adoption of SFT and ensuring the sustainability of agricultural practices.

1.8 Scope of the Study

This study investigates the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, technology awareness, the acceptance of farmers to adopt SFT and food security. The target group of this study are farmers who are cultivating in vegetables and fruits because they are essential to crop production in Sarawak, which can provide nutrition and job opportunities and generate income for farmers (Dardak et al.,2022). This study was conducted in Kuching, Sarikei, Samarahan, Serian, and Kapit because these divisions yield high production of vegetables and fruits (Department of Agriculture Malaysia, 2022). This study employed online and face-to-face questionnaires survey to collect the data. This study focuses on the factors influencing the acceptance of farmers to adopt smart farming technologies in sustaining food security in Sarawak. The

respondents were active farmers residing in Sarawak, Malaysia. Farmers are recognised as the main actors with direct involvement in agriculture productivity.

1.9 Conceptual Definitions of the Variables

The following definitions provide additional explanations for significant terminology used in this study, which are given below:

1.9.1 Performance Expectancy

Schukat and Heisi (2021) described performance expectancy as the extent to which smart farming technologies enhance the practicality, efficacy, functionality, and convenience of agriculture for producers.

1.9.2 Effort Expectancy

Effort expectancy is defined as the ease of use or the ability to be skilled at using smart agricultural technologies (Ronaghi & Forouharfar, 2020).

1.9.3 Social Influence

Social influence in this context pertains to the persuasive effect that the viewpoints, actions, and preferences of influential persons or connections within a person's social network have on moulding their decision-making process regarding the adoption of smart farming technology (Ronaghi & Forouharfar, 2020).

1.9.4 Facilitating Conditions

Ronaghi & Forouharfar (2020) described facilitating conditions as the resources or facilitating elements that contribute to the efficacy and simplicity of employing these sophisticated agricultural instruments within the framework of smart farming technologies adoption.

1.9.5 Food Security

The ability to consistently produce sufficient and affordable food to meet the needs of its population (Hayat, 2021).

1.9.6 Technology Awareness

Shuhaiber and Mashal (2019) defined awareness as an understanding that allows the user to reduce uncertainty subjectively.

1.9.7 Technology Acceptance

The level of acceptance of a novel technology among farmers is primarily indicated by their behavioural intention to utilise the particular technology (Schukat et al., 2019; Ambong & Paulino, 2020).

1.10 Organisation of the Study

Chapter 1 discusses the research introduction, including the background of the study, problem statement, research gaps, research objectives, research questions, the scope of the study, research significance, definition of terms, and the organisation of the study.

Chapter 2 provides a comprehensive review of the pertinent literature, thereby illuminating the existing research gaps. The chapter consists of the definition of food security, how to sustain food security, the definition of smart farming technologies, the impact of SFT, the acceptance of farmers to adopt SFT, and technology awareness. This chapter will also discuss the theory of UTAUT, its conceptual framework, and its hypotheses.

Chapter 3 discusses the application of a sophisticated structured methodology to systematically and scientifically investigate and explore diverse facets of the encompassing environment. Following a succinct summary of the present condition of research designs,

the chapter proceeds to provide a comprehensive elucidation of the particular design employed in the present investigation. Target population, sampling method, sample size, operationalisation construct and measure, questionnaire design, pre-testing, pilot study, and data collection methods are all elements of the established research design. The concluding segments of this chapter provide a comprehensive description of the data analysis techniques that will be employed in the course of this research inquiry.

Chapter 4 pertains to the presentation of the empirical findings of the investigation. The empirical findings of the investigation are presented. SPSS is utilised to conduct the descriptive analysis, and Smart-PLS 4.0 is subsequently employed to evaluate the models, specifically the measurement model and structural model. A concise explanation and argument of the specific measures, threshold values, and the result are followed by additional analysis of the completed tests.

Chapter 5 provides a concise overview of the research, summarising the important discoveries made in the preceding chapter. Subsequently, the chapter elucidates the theoretical and practical implications of the study. This chapter additionally addresses the research limitations and offers suggestions for prospective studies. It concludes with an overarching summary.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This section provides a comprehensive review of the pertinent literature, thereby illuminating the existing research gaps. The chapter consists of the definition of food security, smart farming technologies, the impacts of smart farming technologies, the acceptance of farmers to adopt smart farming technologies, and technology awareness. This chapter also comprises discussions on the review of the theory, theory of UTAUT, conceptual framework, and hypotheses.

2.2 Food Security

Food security is defined as a consistent and free physical access, socio-economic viability to obtain an adequate sum of nutritious and safe food that meets their dietary needs and choices, which promotes a dynamic healthy lifestyle (FAO, 1996). In addition, food security also described the ability to consistently produce sufficient and affordable food to meet the needs of its population (Hayat, 2021). In the context of Malaysia, it is evident that the issue of escalating food insecurity is pervasive and affects the entire population without any exemptions. Malaysia exhibited a moderate level of hunger, as indicated by a slight rise in the hunger index from 10.9 in 2014 to 12.5 in 2022 (Global Hunger Index, 2022). The concept of food security in Malaysia is commonly understood as the capacity to meet its food demands exclusively through domestic production. This perspective suggests that the government's approach to food security primarily revolves around relying solely on domestic sources without seeking external supplementation.

Food security encompasses four primary dimensions: availability, access, affordability, and utilisation. Food availability refers to an adequate supply of food in both formal and informal market settings, satisfying the needs of both individuals and the overall market demand (Hassan & Kam, 2022). Additionally, this involves augmenting local food production and relying on imported sources. Food accessibility refers to the possession of adequate resources, encompassing both economic and physical means, that enable individuals to get an ample supply of food necessary for maintaining a healthy diet (Acheampong et al., 2022). This has implications for an individual's capacity to gain their food requirements promptly and consistently. Food access for smallholder farmers primarily occurs through various means such as self-production, gifting, exchange, borrowing, receiving food aid, and purchasing. Substantial evidence shows that many smallholder farmers rely predominantly on their agricultural output, potentially constraining their ability to get food outside their production scope (Huang & Tian, 2019; Nchanji & Lutomia, 2021). Food utilisation refers to the way individuals or households employ food items that are both available and accessible to them (Hassan & Kam, 2022). Food stability, conversely, includes the characteristics of constant availability, accessibility, and consumption of foods (Acheampong et al., 2022). Van Meijl et al. (2020) argued that the significance of nutrition extends beyond its mere quantity, encompassing factors such as physical and financial accessibility and the consistent utilisation of food through effective processing and preparation practices. The stability of these three components further contributes to the overall food situation (Hassan & Kam, 2022).

Furthermore, Adnan et al. (2019) suggested that to sustain food security, the adoption of technological advancement has impacted the dynamics of human activity in all sectors to increase productivity, particularly in the agricultural industry. In the context of rice, for

instance, ten metric tons per hectare of potential rice production can be attained through new technological advancements such as smart farming technology by using precision farming or the IoT. Additionally, Zainal et al. (2021) and Mohamed et al. (2022) highlighted that IoT implicates using hi-tech apparatus such as software, implant sensors, and other communicational technologies and data transferring devices, and all operate via the internet. In this case, Mohamed et al. (2022) supported the idea that IoT can increase productivity. In addition, a previous study on the adoption of agriculture technology shows that it positively impacts farmers' food security in underdeveloped nations (Hasan et al., 2018).

Moreover, the availability of enhanced and high-performing seed varieties may improve agricultural productivity. Scholars emphasise the significance of allocating resources toward plant breeding initiatives and facilitating the dissemination of high-quality seeds to agricultural practitioners. In addition, the adoption of various agricultural advancements, such as the utilisation of enhanced sources, frequently displays characteristics such as increased tolerance to drought, resistance to diseases, and elevated nutritional content, hence enhancing the overall productivity of crops (Lee, 2020; Simtowe et al., 2019; Ullah et al., 2020; Kumar et al., 2020; Mango et al., 2017). Several scholars claim that, especially among smallholder farmers, the application rate of enhanced seed diversities is relatively low (Alene et al., 2009; Krishna & Qaim, 2008). Although improved seeds are considered accessible, cost-effective, and financially beneficial, many smallholder farmers encounter challenges in investing in the technology (Hoogendoorn et al., 2018).

The implementation of IoT technology has positive outcomes for farmers in various aspects, such as facilitating soil analysis, providing accurate weather predictions, automating water management systems, and enhancing crop quality (Verma & Usman, 2016). Infinitely, technological advancements have the potential to significantly benefit farmers in their daily

operations by diminishing labour expenses, enhancing farm management capabilities, facilitating time and energy conservation, improving efficiency, augmenting farmers' income, and bolstering overall farm productivity (Elijah et al., 2018).

2.3 Technology Acceptance

The concept of technology acceptance refers to the degree to which individuals or organizations are willing to embrace and use new technologies (Davis, 1989). This concept is critical in understanding how and why new technologies are adopted or resisted. Several theoretical models have been developed to explain the factors that influence technology acceptance, with the most prominent being the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT).

TAM focuses on perceived usefulness (PU) and perceived ease of use (PEOU), positing that these factors influence attitudes towards technology, which in turn affect the intention to use and actual usage behaviour. UTAUT expands on this by including performance expectancy, effort expectancy, social influence, and facilitating conditions, moderated by factors such as gender, age, experience, and voluntariness. Key factors influencing technology acceptance include perceived benefits (enhanced performance and convenience), ease of use (user interface design and training support), social influence (peer pressure and cultural factors), facilitating conditions (infrastructure and technical support), and individual differences (demographics and psychological traits).

The degree of acceptance of new technology by farmers is mostly determined by their inclination to utilize the specific technology (Schukat et al., 2019; Ambong & Paulino, 2020). Applications of technology acceptance span various fields, such as understanding

enterprise software usage in information systems, citizen adoption of e-government services, healthcare professionals' use of electronic health records, e-learning adoption in education, and consumer acceptance of new gadgets. These insights guide the design, implementation, and promotion of technological innovations, enhancing user adoption and satisfaction across different domains. Based on prior studies (Wee & Lim, 2022; Schukat et al., 2019) the acceptance models should consider the agricultural context of end users.

Previous studies shows the performance expectancy has a significant where farmers perceive smart farming technologies proficiently facilitate efficient task completion and enhance agricultural productivity, leading to increased income and improved yield, both in quality and quantity (Wee & Lim, 2022; Schukat & Heise, 2021; Beza et al., 2018). In contrast, Sa'ari et al. (2018) found a negative correlation between farmers' acceptance of sustainable farming technologies and their performance expectancy. For effort expectancy, there were a positive impact of IoT adoption on the perception of usefulness and effort expectancy, influencing individuals' behavioural intention (Pillai & Sivathanu, 2020). In addition, a social influence and the intent to adopt SFT have a more excellent significant relationship (Wee & Lim, 2022), as well as the relationship between behavioural intention and behaviour to use smart products (Schukat & Heise, 2021). Additionally, previous study also revealed a significant positive impact of facilitating condition on both behavioural intention and actual use behaviour of smart products (Schukat and Heisi, 2021). It is found that the influence of facilitating conditions is a stronger predictor of cotton farmers' behavioural intention (Li et al., 2023).

2.4 Smart Farming Technologies (SFT)

Agriculture is among the sectors undergoing a significant transformation as a result of Industry 4.0, the fourth industrial revolution. The strategic initiative encompasses the incorporation of a range of emergent digital technologies, namely Internet of Things (IoT), artificial intelligence (AI), augmented reality (AR), digital twins (DT), system integration (SI), big data and analytics (BDA), cloud computing (CC), cyber-physical systems (CPS), simulation, autonomous robotic systems (ARS), wireless sensor networks (WSN), and additive manufacturing (AM). Its purpose is to facilitate digitalisation in various industries (Aceto et al., 2017). Incorporating these technologies in the agricultural sector is giving rise to the advancement of agriculture industries as Agriculture 4.0, which is signified as digital farming, smart agriculture, or smart farming.

This study primarily emphasises the simultaneous enhancement of productivity, profitability, and conservation of natural resources to ensure sustainable food production and address the challenges posed by climate change (Himesh et al., 2018; Sott et al., 2020). The implementation of digital technologies is crucial for the advancement of smart farming. These technologies should be integrated into various agricultural production, processing, and promotion aspects throughout the value chain. This integration aims to optimise the utilisation of resources. For instance, the utilisation of Unmanned Aerial Vehicles (UAVs), machine learning, geospatial technology in agriculture (Sott et al., 2020), internet and broadband connectivity (Bowen & Morris, 2019), computing (Bolfe et al., 2020), big data analytics (Bernhardt et al., 2021), and software-driven management systems (Pauschinger & Klauser, 2022) signifies a deviation from conventional approaches.

There has been a growing and sustained interest in smart farming to improve the operational efficiency of agriculture activities (Klerkx et al., 2019). Several academic studies

underscore the importance and benefits of smart farming. For instance, Himesh et al. (2018) highlighted its capacity to enhance the farm-to-table concept. Pauschinger and Klauser (2022) emphasised its ability to improve performance by minimising uncertainties in food production. Bolfe et al. (2020) focused on the socio-economic development potential of smart farming, while Shogentsukova and Shogentsukov (2023) discussed the shift away from human labour towards the utilisation of digital technologies such as sensors, digital cameras, and coding.

2.4.1 Impact of the Smart Farming Technologies (SFT)

The concept of Smart Farming (SF) pertains to an agricultural approach that utilises capital-intensive and advanced technology to cultivate food in an environmentally friendly and sustainable manner, aiming to meet a large population's needs. This approach is primarily based on the use of IoT (Ibrahim et al., 2018). SFT allows farmers to minimise waste and improve productivity by utilising IoT, big data, and automation technologies. This is achieved by lowering the frequency of farm vehicle rides, minimising errors made by farmers, and optimising the time spent on field labour (Ibrahim et al., 2018).

A prior investigation on IoT technology showed its positive impact on enhancing revenue and efficiency within the services, logistics, and manufacturing sectors (Lee & Lee, 2015). Numerous studies have been conducted on a global scale to acquire a comprehensive understanding of IoT adoption in various contexts. These contexts include the IT smart home service (Rock et al., 2022), the manufacturing industry (Sam et al., 2021), elderly healthcare wearables based on IoT (Sivathanu, 2018), the healthcare technology product (Karahoca et al., 2018), Italian banks adopted IoT (Ammirato et al., 2018), the agriculture industry and the agriculture supply chain in different countries adopted IoT (Jayashankar et al., 2018).

Additionally, the implementation of technological advancements in agricultural practices has been found to have a beneficial influence on food security and welfare. According to Mutungi et al. (2023), the utilisation of drying tarpaulins and airtight storage methods has resulted in a notable enhancement in the availability of food, accessibility to food, household incomes, and the introduction of mechanised shelling techniques has led to a substantial increase in food expenditures by 49 percent and overall spending by 68 percent. A previous study conducted by Gitonga et al. (2013) used propensity score matching to investigate the impact of metal silo adoption in Kenya. The findings revealed that this intervention led to a minimum one-month reduction in the duration of food insecurity. Furthermore, it is worth noting that increased production levels are more financially helpful due to the economies of scale (Manda et al., 2015; Abdulai & Huffman, 2014; Gitonga et al., 2013). In addition, the imperative adoption of technologies is a critical factor in ensuring the maintenance of food security.

In India, implementing IoT technology can revolutionise several facets of agriculture, including farm monitoring, intelligent greenhouses, water and soil quality, scientific disease and pest surveillance, managed use of fertilisers, irrigation management, tracking of assets, remote control, and diagnosis. IoT in these areas is projected to significantly enhance food production by approximately 70 percent, thereby enabling the provision of sustenance for a population of 9.6 billion individuals, which is predicted that around 2 billion sensors will be utilised across 525 million farms (Ahmad et al., 2018). In addition, the integration of IoT technology can provide farmers with technological automation and decision-making tools that encompass knowledge, services, and products to improve the quality, efficiency, and cost-effectiveness of agricultural practices (Elijah et al.,

2018). According to Acheampong et al. (2022), agricultural technology significantly enhanced crop type.

Table 2. 1: Summary of the Impact of Smart Farming Technologies to Sustain Food Security

Author	Country	Factor	Contribution and benefit
Mutungi et al. (2023)	Tanzania	Post-harvest technologies	Availability of food, accessibility to food, household incomes, and the introduction of mechanised shelling techniques.
Ahmed et al. (2018)	India	Internet of Things for Precision Agriculture Technologies	Increase of food production by approximately 70 per cent.
Teklu et al. (2023)	Eutopia	Climate Smart Agriculture Innovation	A notable synergistic impact on crop rotation and the cultivation of improved varieties that exhibit consistent traits.
Mwungu et al. (2018)	Tanzania	Climate Smart Agriculture	Improved varieties and the application of manure, as well as the practice of agroforestry and the utilisation of improved varieties.
Elijah et al. (2018)	India	Internet of Things	Can offer farmers technological automation and decision-making tools that effectively integrate knowledge, service, and products to enhance the quality, efficiency, and cost-effectiveness of agricultural practice.
Wu (2022)	China	New agricultural technology	Have a potential to augment the financial gains of farmers. This is exemplified by the impact of contemporary pesticide and fertiliser technologies.

In the realm of research on the adoption of smart climate agriculture, incorporating agroforestry practices has been found to have a notable synergistic impact on crop rotation

and the cultivation of improved varieties that exhibit consistent traits (Teklu et al., 2023). Similarly, in the previous study, the presence of a positive coefficient of correlation between the utilisation of improved varieties and the application of manure, as well as the practice of agroforestry and the utilisation of enhanced types, suggests the existence of complementary associations among these variables (Mwungu et al., 2018). Implementing novel technological advancements in agricultural practices has the potential to augment farmers' financial gains, exemplified by the impact of contemporary pesticide and fertiliser technologies (Wu, 2022). Moreover, enhancing the adoption rate of novel agricultural technologies can improve the economic advantages derived from farming.

2.5 The Acceptance of Smart Farming Technologies (SFT) by Farmers

The acceptance of technology is contingent upon several factors, including the economic viability of the technology, national policies, and the legal landscape that arises as a consequence of these policies. The level of acceptance of a novel technology among farmers is primarily indicated by their behavioural intention to utilise the particular technology (Schukat et al., 2019; Ambong & Paulino, 2020).

According to Schukat and Heisi (2021), prior research demonstrated that the behavioural intentions of farmers significantly impact their likelihood of adopting and utilising smart agricultural products. The behaviour of farmers is contingent upon various factors, with social influence emerging as the most influential determinant of behavioural intention (Ronaghi & Forouharfar, 2020). Blasch et al. (2020) conducted a study that examined the adoption of technology by farmers based on the characteristics of the technologies, specifically focusing on the advantages and benefits they offer. Furthermore, a study by von Veltheim et al. (2022) examined the behavioural intention affected by social

influence on German farmers to adopt autonomous field robots. However, prior research has shown that performance expectancy adversely affects the acceptance of farming technology (Sa'ari et al., 2018). The establishment of the technological infrastructure, support facilities within public departments, and favourable environments have potentially positively influenced individuals' behavioural inclination to adopt the technology (Ronaghi & Forouharfar, 2020).

According to Venkatesh et al. (2012), the utilisation or adoption behaviours is influenced by individual age and experience are impacted by FC. Ward et al. (2018) reported that younger individuals with more excellent technological expertise devise strategies to facilitate the favourable reception and utilisation of technology. Venkatesh et al. (2003) proposed that the impact of facilitating conditions on the actual use or adoption of the innovation is controlled by age and experience. Beza et al. (2018) found that older farmers exhibited a more substantial impact of facilitating conditions on their behavioural intent.

Moreover, the UTAUT framework posits that intention results from individuals' perceptions of technology PE, SI, EE, and FC. Moreover, TPB proposed an outline comprising three distinct factors that contribute to the development of a person's intention to adopt a particular behaviour. These factors include the person's attitude towards the specific behaviour, the perceived level of control over the behaviour, and the subjective norm associated with the behaviour. Moreover, intention is the subjective likelihood that a person will act or behave (Ajzen, 1991). Conversely, Venkatesh et al. (2003) stated that behavioural intention (BI) refers to the inclination to exert effort in attempting or adopting a particular technology over time. Behaviour intention differs significantly from desire and self-prediction, as noted by Milne et al. (2002). BI is the immediate precursor to a particular action's actual behaviour or adoption. The classification of both goal intention and

implementation intention is necessary. One fundamental aspect of behavioural intention involves the inclination to partake in a specific behaviour, such as “I intend to increase my level of play”. Conversely, the concept of implementation intention pertains to the consideration of factors, such as the how, when, or other specific measures that enhance the likelihood of engaging in the behaviours (Milne et al., 2002). For instance, “I intend to engage in a recreational activity for three hours daily starting in the upcoming month”. According to Webb and Sheeran (2006), the implementation is considered to have a more significant influence on performing the intended behaviours.

Previous research has yielded significant and positive findings BI in various contexts. For example, Michels et al. (2020) observed the adoption of internet-enabled mobile devices among farmers in Germany, while Mulugo et al. (2019) examined farmers' utilisation of banana tissue culture planting materials. Additionally, Schukat and Heisi (2021) investigated the acceptance of smart products, Wee and Lim (2022) explored the adoption of smart farming technologies, Wang et al. (2019) examined the usage of agricultural information technology, and Ronaghi and Forouharfar (2020) investigated the utilisation of IoT. Some observed that young farmers and individuals affiliated with universities are more inclined to adopt new technologies. In addition, perhaps young farmers possess more excellent knowledge and can effectively adapt to the ever-evolving technological landscape within the agricultural sector. This enables them to expedite the adoption of smart farming technologies, resulting in various advantages, such as increased monthly income, enhanced profitability and efficiency of agricultural operations, and decreased labour expenses. However, Tagaki et al. (2020) pointed out that the socio-demographics of farmers have no impact on the adoption intention.

Nevertheless, the behavioural adoption refers to the practical utilisation of technology, subsequently reported as the tangible acceptance and implementation of the technology or the demonstration of expected behaviours by the individual being surveyed. To assess user behaviour, researchers employed various measures such as binary responses such as ‘yes’ or ‘no’ or quantitative indicators such as time spent using the technology (Venkatesh & Davis, 2000) or frequency of use (Venkatesh et al., 2012). According to Ebrahimi Sarcheshmeh et al. (2018), a notable positive correlation exists between adoption behaviour and the utilisation of nuclear technology in the agricultural sector. Similarly, the behavioural intention and the actual use of smart products have a positive relationship (Schukat & Heisi, 2021), the adoption of pressurised irrigation technology (Nejadrezaei et al., 2018), the utilisation of crop protection smartphone applications (Michels et al., 2020), and the usage of IoT technology examined (Ronaghi & Forouharfar, 2020).

2.6 Technology Awareness as a Moderator

Shuhaiber and Mashal (2019) defined awareness as an understanding that allows the user to reduce uncertainty subjectively. It has a potential impact on the adoption of smart technologies. In addition, technology awareness also performs a significant role in determining the acceptance behaviour of farmers, particularly in terms of their familiarity with a specific technology (Kamarul Zaman et al., 2023). Due to a lack of cognisance and adequate knowledge from credible sources, the farmers are forced to trust input sources for information (Ullah et al., 2020a).

Farmers’ skills, knowledge, and technology awareness on this matter are also critical because farmers are the main actors in the production of agricultural products. According to Suebsombut et al. (2020), the concept of smart agriculture involves the application of

intelligent and digital methodologies to effectively monitor, optimise, and regulate many aspects of agricultural production. The current management of farms necessitates a strong understanding of smart agricultural technology since farmers must actively enhance their knowledge and skills to implement these advanced technologies in their farming practices effectively. However, it is essential to note that every farmer possesses unique talents and experiences when using smart agricultural technology. According to Ghosh et al. (2020), farmers still need training to guide them in agriculture activities, especially in technologies, because many farmers have little knowledge. It is vital to provide individuals with training and education to familiarise them with the most recent advancements in fundamental technologies. Training on operating and using the SFT can help them utilise their farm well.

Prior research has shown that technology awareness at a high level is crucial for individuals to embrace technology, and moderating technology awareness is significant among the identified relationships in the constructive variables (Daniali et al., 2022; Alaeddin & Altounjy, 2018). Nevertheless, more knowledge is needed to ensure adequate awareness regarding the adoption and progress of emerging technologies, hindering individuals from accessing potential benefits and advantages (Alaeddin & Altounjy, 2018). According to Abubakar and Ahmad (2015), based on a study of the behavioural intentions to use Point of Sales (POS) terminals in Nigeria showed a negative relationship moderate effect of technology awareness between facilitating conditions and the behavioural intention to use POS. However, several studies stress the factors influencing farmers' awareness of CSA and the behavioural environment (Mustafa et al., 2018; Suleswski & Golas, 2019; Walder & Kantelhardt, 2018). Additionally, these studies highlight the importance of farmers' knowledge and beliefs, particularly their perception that the actions are user-

friendly and manageable. Gebaska et al. (2020) emphasised the significance of knowledge acquisition in raising farmers' awareness regarding using agricultural technologies.

Furthermore, a research investigation into the utilisation of renewable energy sources revealed that the level of awareness exhibited a noteworthy and favourable impact on the inclination to adopt such practices among rural households in Iran (Rezaei & Ghofranfarid, 2018). As previously shown, the establishment of awareness is widely recognised as the initial and pivotal factor essential for achieving success in endeavours which is aimed at modifying behaviour. A heightened level of consciousness empowers individuals to make well-informed decisions and concurrently enhances acceptance of technological advancements (Ullah et al., 2022). In addition to this, farmers must be equipped intentionally with easily accessible and accurate information. Moreover, the implementation of extensive training initiatives and community awareness programs, specifically using mass media platforms like radio and television, can effectively promote the potential benefits of SFT applications in agricultural practices.

2.7 Review of the Technologies Acceptances Theory

2.7.1 Theory of Reasoned Action (TRA)

The theory of Reasoned Action (TRA) is utilised by numerous researchers across a wide range of academic fields. This researcher recognised the insufficiency and numerous limitations of this theory. As stated by Kurland (1995), the limitation of TRA lies in its presumption that all actions are entirely controlled by volition. This assumption neglects to recognise that systemic constraints, for instance, may exert an influence on the behaviours of individuals. The Theory of Reasoned Action (TRA) is considered to be quite general, as stated by Davis et al. (1989). TRA, according to Baraghani (2008), is a comprehensive

paradigm in which the beliefs underlying a specific behaviour are not specified. Prior to employing TRA, Salem Al-Mamary et al. (2016) stated that researchers must ascertain the subjects' salient beliefs concerning the behaviour being examined.

2.7.2 Technology Acceptance Model (TAM)

Davis et al. (1989) developed the technology acceptance model (TAM) to predict an individual's willingness to adopt and endorse information systems and technology. TAM, an extension of the Technology Acceptance Model (TRA), is particularly designed to address the acceptability of information system technology (Davis, 1989). Notably, TAM is simpler compared to the major models TRA and TPB. The TAM framework comprises two key constructs: Perceived Usefulness and Perceived Ease of Use. Perceived Usefulness assesses an individual's belief in the system's ability to enhance work performance (Surendran, 2012). Perceived Ease of Use relates to an individual's perception that using a specific system would require minimal effort. External factors, including social, cultural, and political considerations, influence these two variables. Social elements encompass language, skills, and supportive environments, while political variables involve politics and political crises. The term attitudes refer to the user's evaluation of adopting a particular technology, while behavioural intention quantifies the likelihood of an individual using the technology (Chen et al., 2017).

TAM has been widely used by researchers to characterise diverse categories of information systems. For example, TAM and modified TAM models have been applied to analyse user behaviour in various contexts, such as teachers using e-learning systems, acceptance of online shopping and e-commerce, online banking systems, e-service adoption, and the acceptance of Radio Frequency Identification (RFID) (Davis, 1989; Lokuge et al., 2018; Chen et al., 2017).

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

Venkatesh et al. (2003) introduced the Unified Theory of Acceptance and Usage of Technology (UTAUT) model, a response to the limitations of the Technology Acceptance Model (TAM) by integrating social aspects and human behaviours. A study by Caffaro et al. (2020) investigated the influencing factors on ICT acceptability, behavioural intention, and actual usage. While the predictive capability of TAM and its extensions is limited to 40%, the UTAUT model demonstrates a higher predictive capability of 70% (Holden & Karsh, 2010). Formulated on four key factors for instance, performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). The UTAUT model is enhanced by additional stimuli such as gender, age, experience, and voluntariness of usage (Venkatesh et al., 2012; Wee & Lim, 2022; Ronaghi & Forouharfar, 2020).

These factors collectively shed light on the human perspective concerning the acceptance of smart technologies (Kim et al., 2014). The UTAUT model has been previously applied in various agricultural contexts, revealing significant predictors of behavioural intention among farmers in studies related to SFT, IoTs in smart farming, and the adoption of crop protection smartphone apps (Wee & Lim, 2022; Ronaghi & Forouharfar, 2020; Michels et al., 2020).

Thus, by considering the high potential of the UTAUT model in predicting the intention to use new technologies as well as its frequency of application in the agricultural context, the researchers of this study decided to use the UTAUT model.

2.8 Theoretical Framework

Bacharach (1989) defines theory as a delineation of the interconnections between concepts, bounded by a set of assumptions and constraints. Beyond that, it functions merely

as a linguistic device to structure an intricate empirical realm. This section comprises the foundational detailed explanation of the theory pertaining to the investigation of UTAUT and the moderator, technology awareness.

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

This present study employs UTAUT as the foundational or underlying theory to investigate the factors influencing the acceptance of farmers to adopt SFT in sustaining food security. In 2003, Venkatesh and his colleagues planned a novel technology acceptance model after thoroughly examining and comparing eight existing models, known as the Unified Theory of Acceptance and Use of Technology (UTAUT). Venkatesh et al. (2003) suggested a model grounded in an empirical analysis of longitudinal research conducted across four distinct organisations. The data used in this study is collected over three different periods. The researchers determined that social influence, effort expectancy, performance expectancy, and facilitating conditions have an encouraging and substantial impact on behavioural intention and use behaviour. Furthermore, the study conducted by Venkatesh et al. (2003) shows that the use of demographic features (gender, age, voluntariness, and experience) of the respondent plays a significant moderating role. Figure 2.1 shows the theoretical framework of the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003).

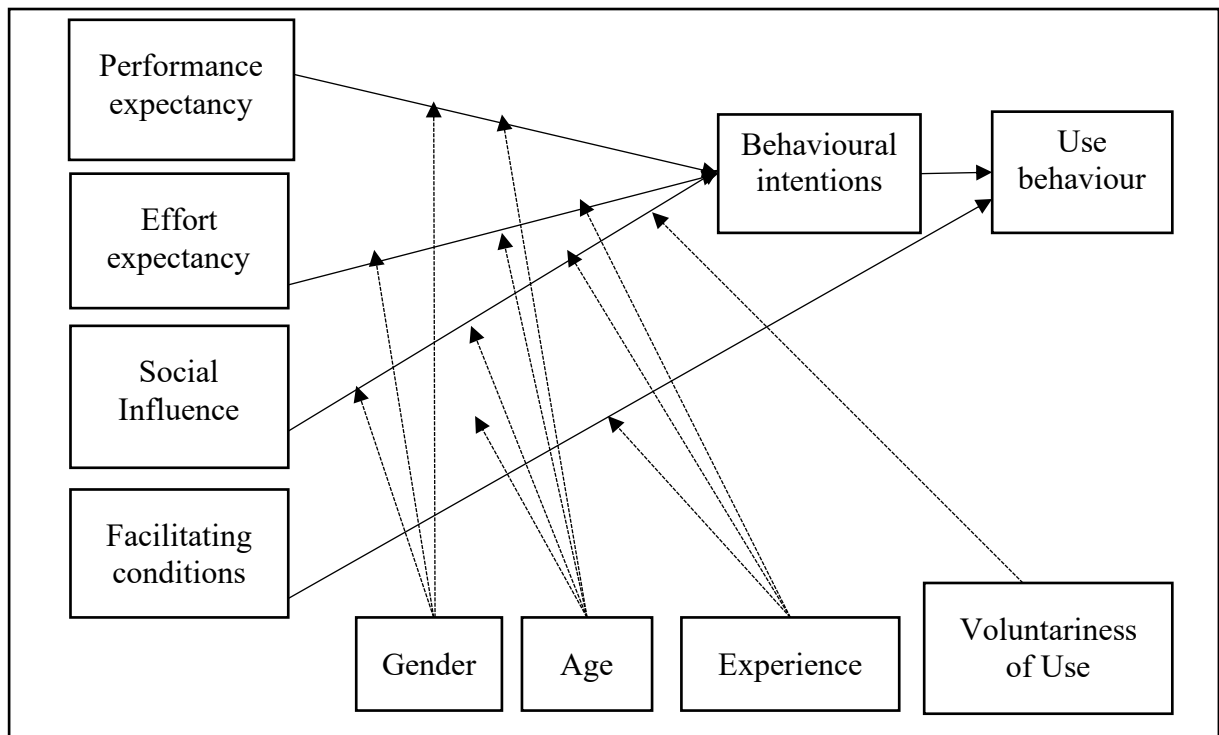


Figure 2. 1: Theoretical Framework of the Unified Theory of Acceptance and Use of Technology (UTAUT)
Source: Venkatesh et al. (2003)

According to Venkatesh et al. (2012), the initial structure comprises performance expectancy (PE), social influence (SI), effort expectancy (EE), and facilitating conditions (FC). In addition, it has been determined that PE, SI, EE, and FC significantly influence use behaviour and behavioural intentions. Wei and Lim (2022) have identified four distinct factors that have been linked in prior research to the adoption of smart agricultural technologies by farmers.

Subsequently, after applying UTAUT, further examination using UTAUT2 is carried out; UTAUT2 is another model developed by Venkatesh et al. (2012). After careful consideration, it is decided that additional constructs such as hedonic motivation, price value, and habit are inappropriate for this study at the current timeline; nonetheless, it has the potential for extended research in the future. Hedonic motivation is the enjoyment of

technology application, regardless of the outcome (Khatimah et al., 2019; Schukat & Heisi, 2020). Nevertheless, price value pertains to the trade-off between a technology's advantages and its monetary price (Venkatesh et al., 2012). Moreover, farmers may need to experience whether the price change influences their behavioural intention. Then, a habit is described as the extent to which individuals behave spontaneously as a learning outcome (Venkatesh et al., 2012). These three concepts pertain to actual technology applications and are vital in evaluating technology acceptance and use behaviour. Moreover, the implementation of SFT in Sarawak still needs to improve, resulting in a limited understanding of this agricultural technique among farmers (Wee & Lim, 2022). Hence, the UTAUT2 theory and its supplementary constructs are insignificant in the present research study.

Additional evidence supports the UTAUT's superiority over alternative models, as demonstrated by empirical research in the past. This can be attributed to the reliability and consistency of its foundational constructs in predicting the intentions and perceived usefulness of system utilisations. An extensive validation of UTAUT was conducted over an extended period of time (Venkatesh et al., 2003). According to their findings, UTAUT explained approximately 70% of the variance observed in the intention to utilise technology and behaviour of individuals, and approximately 50% of the variance observed in their actual utilisation of said technologies. Prior studies by Slade et al. (2015) and Abubakar and Ahmad (2013) have concentrated primarily on determining an individual's intention to employ a system prior to its implementation. As a result, the present inquiry finds this theory to be pertinent. Despite its limitations, UTAUT has acquired widespread practice, expansion, and integration in empirical research for implementing various information and communication technologies (Baishya & Harsh, 2020; Dwivedi et al., 2017). Furthermore, previous research has extensively employed UTAUT to explain the influencing factors on the behavioural

intention of various technologies, including the acceptance of specific farming technologies (Li et al., 2020) and the implementation of blockchain in smart agriculture (Ullah, 2021). In a recent study, Wei and Lim (2022) examined the farmer's behavioural intention toward smart farming, then revealed that social influence emerged as the most influential factor in predicting behavioural intention. Similarly, von Veltheim et al. (2022) investigated the intention to use autonomous field robots to significantly impact PE, SI, EE, FC, and behavioural intention to embrace technologies in agriculture. Therefore, UTAUT can be an effective tool for evaluating the various aspects that influence farmers' adoption of SFT to sustain food security.

2.9 Factor Influencing the Acceptance of Farmers to Adopt SFT

2.9.1 Performance Expectancy

Performance expectancy (PE) is a crucial determinant that influences the user's decision to adopt an innovation or engage in any behavioural change associated with technology or practice (Venkatesh et al., 2003). Schukat and Heisi (2021) described performance expectancy as the extent to which smart farming technologies enhance the practicality, efficacy, functionality, and convenience of agriculture for producers.

Moreover, the degree to which an organisation or firm considers using technology to enhance performance and productivity is also a significant factor (Ameen et al., 2019). Furthermore, other theories also employ the concept of PE. For example, the TAM and its subsequent version, TAM2, employ the concept of perceived usefulness, while the DOI theory uses relative advantage (Venkatesh & Davis, 2000). Venkatesh et al. (2003) reported the existence of similarities between previous constructs and their underlying interpretations. The construct of perceived ease of use has shown strong predictive capabilities in

determining the likelihood of individuals adopting intentions in both mandatory and voluntary work environments (Venkatesh et al., 2012).

Performance expectancy (PE) is determined as a critical factor inducing the behavioural intention to adopt smart farming technologies in various prior studies. These studies find that farmers perceive smart farming technologies proficiently facilitate efficient task completion and enhance agricultural productivity, leading to increased income and improved yield, both in quality and quantity (Wee & Lim, 2022; Schukat & Heise, 2021; Beza et al., 2018). Furthermore, the farmers concurred that implementing technologies has the potential to alleviate a range of tasks, varying from partially to entirely (Schukat & Heise, 2021). In contrast, Sa'ari et al. (2018) found a negative correlation between farmers' acceptance of sustainable farming technologies and their performance expectancy. Multiple studies documented that the adoption of a particular technology leads to enhanced performance and increased productivity in the production output of the respective product (Wee & Lim, 2022; Schukat & Heise, 2021). Therefore, if an organisation believes that adopting a particular technology will enhance its performance, it is highly probable to adopt it. However, if an organisation believes implementing the technology will not improve its overall performance, the probability of adopting it is diminished.

2.9.2 Effort Expectancy

Effort expectancy (EE) is defined as the level of simplicity and ease allied with the utilisation of technology (Venkatesh et al., 2003). EE is defined as the ease of use or the ability to be skilled at using smart agricultural technologies (Ronaghi & Forouharfar, 2020). The potential for decreased user exertion has accompanied the introduction of innovative approaches and proposed novel practices. The concept of perceived ease of use is commonly employed in the theories of TAM and TAM2, while the complexity construct is used in the

DOI theory (Venkatesh & Davis, 2000). The significance of these two constructs, as shown by their definitions, measurement scales, and the influence of ease of use and complexity, has been established as a critical element of individuals' intention to adopt various technologies in different adoption scenarios (Venkatesh et al., 2003). The significance of effort reduction in the early stages of innovation adoption outweighed its importance in the later stages of the innovation phase (Rogers, 2003).

In addition, implementing technological advancements has the potential to ease the intricacies associated with daily professional routines, owing to their user-friendly nature and simplified operational procedures. Previous research conducted by Pillai and Sivathanu (2020) has shown a noteworthy positive impact of IoT adoption on the perception of usefulness and effort expectancy, influencing individuals' behavioural intention. The utilisation of IoT technologies in the agricultural sector proves helpful in various aspects, such as the anticipation of natural disasters, crop monitoring, assessment of fertiliser needs, and facilitation of decision-making processes about farming. Furthermore, the implementation of various farming practices has been found to enhance farm productivity (Verma & Usman, 2016; Ahmed et al., 2018). The significance of technology's utility cannot be overstated, as farmers actively seek it out before its adoption.

The high utility of the technologies will influence their widespread adoption by producers. Beza et al. (2018) found a positive correlation between effort expectancy and behavioural intention. This indicates that farmers who believe transmitting SMS requires little effort strongly intend to use mobile SMS for the data pool. Therefore, technologies that are easily manipulated and accessible are crucial in the agriculture sector, where participants range from the elderly to the young. Furthermore, instruction and training for farmers on

how to operate the technologies are crucial because they can help them gain a deeper understanding of the technologies they will employ.

2.9.3 Social Influence

Social influence (SI) in this context pertains to the persuasive effect that the viewpoints, actions, and preferences of influential persons or connections within a person's social network have on moulding their decision-making process regarding the adoption of smart farming technologies (Ronaghi & Forouharfar, 2020). Humans are inherently social creatures susceptible to the influence of their social environment and interpersonal interactions (Venkatesh et al., 2012).

The concepts of social norm and SI have been examined in various theoretical frameworks, for instance, the subjective norm employed in the TPB, TRA, and TAM2, as well as the factors related to image in DOI theory (Venkatesh & Davis, 2000). There are similarities between the subjective norm and image (Venkatesh et al., 2003). The conceptualisation remained consistent despite variations in classification. Individuals who hold significance in an individual's life profoundly impact the decision-making process (Ajzen, 1991). The statement as mentioned earlier regarding the implementation of technology and innovation. Moreover, the extent to which an individual is inclined to incorporate new technology into their daily work is influenced by social factors.

According to Beza et al. (2018), the acceptance of the Indian farmer on the IoT-A shows a positive influence by social influence because farmers interact with fellow villagers before deciding whether to adopt the technology. Farmers often rely on their communities to engage in discussions and exchange information regarding the challenges, benefits, and advantages associated with the adoption of new technologies that are unfamiliar to them. For example, individuals establish a group or community via the messaging application

WhatsApp, facilitating the dissemination of knowledge through training sessions and consultations provided by experienced farmers. In a similar vein, previous research has examined the social impact and the intent to adopt SFT have a more excellent significant relationship (Wee & Lim, 2022), as well as the relationship between behavioural intention and behaviour to use smart products (Schukat & Heise, 2021). Additionally, studies have explored the acceptance of sustainable farming technologies (Sa'ari et al., 2018), the adoption of agricultural innovations (Montes et al. et al., 2021), and the influence of social networks on technological adoption (Filippini et al., 2020; Akyuz & Theuvsen, 2020). However, a previous study on the acceptance of oil palm innovation among smallholder farmers has found that the social system has no impact on influencing farmers' acceptance of innovation (Saad & Salman, 2021).

Nevertheless, the social system or SI continues to serve as a significant predictor for farmers, as it exhibits a high level of importance in facilitating technological advancements within the agricultural community. According to Cordaro and Desdoigts (2021), many farmers rely on technical information provided by individuals with whom they share close relationships. In a scholarly investigation on the adoption mechanisms of smart agriculture, it is observed that certain cotton farmers placed significant reliance on their superiors in the decision-making process (Li et al., 2023).

SI plays a significant role in determining adoption intentions (Ajzen, 1991). The adoption of innovation is contingent upon the social impact that facilitates or hinders the adoption of an innovation (Rogers, 2003). SI affects adoptees through three distinct mechanisms: compliance, identification, and internalisation (Venkatesh et al., 2003). Compliance impacts maintaining the status quo. In contrast, the remaining two mechanisms, identification and internalisation, are characterised by behavioural changes resulting from a

shift in beliefs and values or for reasons of social status (Rogers, 2003). Adoption under voluntary circumstances primarily occurs due to internal motivations rather than the attainment of rewards by individuals in positions of authority (Rogers, 2004). The phenomenon of adoption without social support pertains to instances where individuals choose to adopt without the presence of adequate social help. This can be seen as a departure from prevailing social norms or cultural expectations (Ajzen, 1991). Venkatesh et al. (2003) pointed out that social factors influence the intention to adopt technology, while the personal choice to use the technology can also impact this intention. According to Rogers (2003), individual experience, which serves as a determining factor for effectively completing tasks, influences the adoption of innovation rather than relying solely on social factors to determine whether or not to implement the technology.

2.9.4 Facilitating Conditions

Facilitating conditions (FC) is the perception of an organisational and technical facilitation system within the organisation, which aids in the adoption and subsequent utilisation of technology or innovative practices (Venkatesh et al., 2003). Venkatesh et al. (2012) identified facilitating conditions as a direct determinant of user behaviour. Ronaghi & Forouharfar (2020) described the FC as the resources or facilitating elements that contribute to the efficacy and simplicity of employing these sophisticated agricultural instruments within the framework of smart farming technology adoption.

FC is associated with apparent behavioural control in the Theory of Planned Behaviour (TPB) and compatibility with the Diffusion of Innovation theory (DOI) (Venkatesh & Davis, 2000). The primary theme that emerges from these concepts is providing supportive aid that eliminates obstacles to the acceptance or utilisation of technology or innovation (Venkatesh et al., 2003). FC directly influences the adoption or

actual application of the technology, as it influences the individual's understanding from the intention formulation stage to the adoption or utilisation stage (Venkatesh et al., 2012). If effort expectation is excluded from the model, the FC can be used to predict adoption intent (Venkatesh & Davis, 2000). EE is essential to UTAUT, but only FC directly influences adoption (Venkatesh et al., 2003).

Schukat and Heisi (2021) revealed a significant positive impact of FC on both behavioural intention and actual use behaviour of smart products. It is found that the influence of facilitating conditions is a stronger predictor of cotton farmers' behavioural intention (Li et al., 2023). Moreover, it can be observed that farmers who possess a strong foundation for incorporating intelligent agricultural solutions on their farms are more likely to embrace this technological advancement. In contrast, an examination by Beza et al. (2018) on the adoption of short message service (SMS) in agriculture has revealed a low level of significance between FC with respect to behavioural intention. Nevertheless, the significance level is noticed to be greater among older farmers. Previous studies have shown no discernible impact of facilitating conditions (Baptista & Oliveira, 2015; Im et al., 2011). The farmers may not highly prioritise phone SMS for farming data collection, even when there are facilitating conditions such as the availability of resources and support from extension workers (Baptista & Oliveira, 2015).

Table 2. 2: Summary of the Theory in Literature Review

No	Authors	Objective	Method	Theory	Findings
	Ronaghi and Forouharfar (2020)	To identify the factor influencing in the adoption of IoT in smart farming.	Quantitative Smart-PLS	UTAUT	The construct of UTAUT have positive impact towards the intention to use IoT technology.
2	Wei and Lim (2022)	To assess the behavioural intention to use SFT.	Quantitative Smart-PLS	UTAUT	The construct of UTAUT influenced the BI to adopt SFT. SI greater significant on BI.
3	Ullah (2021)	This study aims to examine the main factors that influence an individual's decision to employ block-chain technology for agriculture businesses.	SPSS STATA Smart-PLS	UTAUT	PC, EE, and FC have a significant impact during the blockchain adoption. SI on behavioural intention.
4	Li et al., (2020)	To examine the factors influencing among Chinese farmers' adoption of precision agriculture technologies in cultivation systems and to make recommendations for the future promotion of these technologies.	Surveys conducted via face-to-face interviews. PLS-SEM	UTAUT	The FC the best predictor improving Chinese farmers' willingness to adopt technologies.
5	Li and Cheng (2021)	Determine the underlying mechanism of the factors that influence large and specialised vegetable producers' willingness to	Questionnaires SPSS	UTAUT TOE	PE, EE, SI and FC factors have no significant influence on the willingness to adopt IoT technologies.

		employ technologies.	IoT		Farmers with low education and older farmers specialised in large vegetables farm have low level of awareness on the performance and ease to use the technology.
6	von Veltheim et al. (2022)	To investigate the factors that influence farmers' intent to use autonomous field robotics in the future.	Quantitative Smart PLS	UTAUT	On the BI to use autonomous field robots, PC and SI have a positive impact, while expected effort and anxiety have a negative impact. There is a correlation between age and the intent to use an automation.
7	Beza et al. (2018)	To determine the acceptability of mobile SMS technology for providing farm-related information to smallholder farmers. To determine the significance of farmer characteristics such as experience and age in predicting farmers' intentions to implement mobile SMS.	Quantitative PLS-SEM	UTAUT 2	Farmers who believe sending SMS requires little effort have a strong intent to use mobile SMS for data collection. Social influence would have a positive effect on their behavioural intention to adopt mobile SMS. When there is a facilitating condition (e.g., resources, extension worker support) for farmers to use mobile SMS for agricultural data collection, they do not place a high value on it.
8	Sa'ari et al. (2018)	To enhance the value of the current literature in the investigation of farmers who use sustainable agricultural	SPSS & PLS- SEM Questionnaires	UTAUT	Negative relationship of performance expectancy and sustainable farming technology.

		technology in their businesses and in relation to the national plan.			
9	Michels et al. (2020)	To examine mobile internet adoption among German farmers.	STATA		Farmer's age and the farm size are associated with mobile internet adoption.
10	Pillai and Sivathanu (2020)	To examine the adoption of IoT in the agriculture industry by Indian producers.	PLS-SEM Questionnaires	BRT	The perceived usefulness and social influence have a positive relationship on the IoT-A adoption.
11	Tamirat et al. (2018)	To identify the key socioeconomic drivers on the adoption of precision agriculture in Denmark and Germany.	Binary logit model Cross-sectional Survey data		Farm size, farmer age, and demonstration and networking events, such as seminars and exhibitions are affecting the adoption decision of producers significantly. Younger farmers have higher propensity to adopt technology compared to older farmers.
12	Jayashankar et al. (2018)	Determine trust influences perceived value and risk, and perceived value and risk impact of IoT adoption.	Survey via Qualtric PLS-SEM STATA	TAM	Have a positive significant on IoT adoption.
13	Mozatto et al. (2018)	Specifying ecosystem services or reducing the environmental impacts of intensive agriculture.	Qualitative Meta-analysis	TRA & TPB	Farmers are more motivated to employ EFFPs, particularly organic agriculture. Early adopters are predominantly male, while late adopter are women.

14	Schukat et al. (2019)	To ascertain the factors that influence farmers' intentions to partake in the IAW.	Online questionnaire. Survey, private networks, and social media are used. PLS-SEM, PLS-MGA	UTAUT 2	Behavioural intention is influenced positively by performance expectation, social influence, and facilitating conditions. The relationship between IAW experience and behavioural intention is moderated by age, with the effect being stronger for senior respondents. The correlation between social influence and behavioural relationship is moderated by professional experience.
15	Akyuz and Theuvsen (2020)	To determine the behavioural intentions of Turkish sultana raisin producers toward organic farming practices.	PLS-SEM	TPB & TAM	The subjective norm has a substantial impact on the attitudes of both farmer groups. Positive and significant effects of perceived utility on organic production attitudes are found.
16	Filippini et al. (2020)	To determine whether the networks to which farmers belong, their socio-demographic characteristics, and the scale of their property have an impact on the adoption of smartphones for professional purposes by farmers.	Qualitative multiple linear regression model. Social Network Analysis	-	Farmers tend to assist each other in small, close-knit communities.

17	Cordaro and Desdoigts (2021)	related to two literature streams that address the adoption of technology in family farming.	Qualitative		Farmer's civic capital is significantly and positively associated with agricultural technology adoption even though in a group of membership.
18	Li et al. (2023)	To examine the adoption of SA technologies by cotton framers and the extent of their adoption.	SEM	DTPB	The behavioural attitudes, subjective norms, and perceived behavioural control of cotton producers all contribute to their willingness to adopt SA technologies and can also directly or indirectly influence their behaviours through this willingness.
19	Nejadrezaei et al. (2018)	The purpose of this paper is to investigate the factors influencing the adoption of pressurised irrigation technology by olive producers in Roudbar County.	SPSSV19 and SmartPLSV3 software	UTAUT	There are significant associations between (a) performance anticipation and behavioural intention, (b) social influence and behavioural intention, and (c) facilitating conditions and use behaviour. A significant correlation is also observed between the intention to employ pressurised irrigation technology and its actual implementation.
20	Michels et al. (2020)	This study investigated factors that influence farmers' adoption of crop protection smartphone apps.	PLS-SEM and a binary logit model.	UTAUT	Positive behavioural intent to use an agricultural protection smartphone app.

21	Ebrahimi Sarcheshmeh et al. (2018)	The objective of this study is to conduct a causal analysis of the adoption of nuclear technology in agriculture.	Kruskal-Wallis test	TAM & TAM2	There is a strong correlation between the use of nuclear technology in agriculture and social norms. There is no correlation between the use of nuclear technology in agriculture and adoption propensity and adoption behaviour.
22	Mulugo et al. (2019)	Factors influencing producers' intentions to use banana tissue culture planting materials for Banana Xanthomonas Wilt control.	Questionnaires PLS-SEM UTAUT	-	The primary predictor of intentions to use tissue culture propagation materials is social influence.
23	Jaroenwanit et al. (2023)	To examine the smart farming adoption and risk management.	Questionnaires PLS-SEM Sobel test	TAM IDT	SI positive relationship on the adoption of SF. Intention to adopt of SF positive correlation with risk management.
24	Yoon et al. (2020)	To investigate the impact of the adoption of smart farm in Korea.	Questionnaires	TOE IDT	The result shows the smart farm is not alternative for farm organisations.
25	Michels et al. (2020)	To examine mobile internet adoption among German farmers.	STATA	-	Farmer's age and the farm size are associated with mobile internet adoption.
26	Caffaro et al. (2020)	To identify the factor influencing in the adoption SFT.	PLS-SEM	TAM	Farmers intention to adopt SFT influence by PU.
27	Blasch et al. (2020)	To study on the willingness of farmers to adopt precision farming technologies.	STATA Mixed logit Latent class logit model	TAM	Farm size influence by the PF. Small fam did not influence by the PF, however large farm is strongly influence by PF.

					Older farmers less intention to adopt PF compared to younger farmers. Social influence positive relationship in intention to adopt PF.
28	Tagaki et al. (2020)	To examine the factor influencing farmers to adopt Smart Agriculture.	Ordered logit - model		Socio-demographic of farmers are not significant with farmers adoption intention. Perceived attributes of the new technology such as compatible, easy to use and learn, can increase yield and farm income influencing the farmers intentions.
29	William et al. (2022)	To understand antecedents that influence farmers decisions to adopt smart farming technologies.	PLS-SEM	UTAUT	Government social power is the strongest predictor to usage behaviour. Behavioural intention and usage behaviour have positive relationship
30	Schukat and Heisi (2021)	To foster the understanding of what factors are decisive for farmers in adoption of the technologies.	PLS-SEM PLS-MGA	UTAUT 2	Hedonic motivation influence both of intention to adopt and use behaviour. Behavioural intention is influencing by social and performance factor. Behavioural intention and user behaviour have a positive relationship. Age, work, experience, and farm size are identified influencing the willingness of the farmers to use smart product.

31	Ayaz and Yanartas (2019)	PLS-SEM	UTAUT	Performance expectance and social influence is significant towards behavioural intention. Effort expectancy is insignificant towards behavioural intention.
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2.10 Relevant Works on SFT

The UTAUT framework serves as the theoretical foundation for this work, which is applied to identify the factor influencing the acceptance of the farmers to adopt SFT in sustaining food security in the region of Sarawak. The developed UTAUT model by Venkatesh et al. (2003) is widely recognised as an advanced acceptance model. There are numerous theories about the adoption of technology. Mohamad and Kasim (2019) claimed that UTAUT is a prominent and widely accepted theory in the adoption of consumer technology.

UTAUT model is a comprehensive synthesis of eight influential theories concerning the adoption of technology by users. The aforementioned theories consist of the Motivational Model (MM), Innovation Diffusion Theory (IDT), Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), TPB/TAM combination, PC utilisation model, and Social Cognitive Theory (SCT). It is anticipated that the incorporation of these theoretical frameworks will augment comprehension and elucidation regarding the adoption of technology in scientific investigations (Venkatesh et al., 2003). The user's intention to employ technology and the subsequent behaviour can be understood more thoroughly through the application of a theoretical framework. Four fundamental constructs that significantly influence user adoption and utilisation are identified within this framework. According to Venkatesh et al. (2012), the initial structure comprises performance expectancy (PE), social influence (SI), effort expectancy (EE), and facilitating conditions (FC). In addition, it has been determined that PE, SI, EE, and FC significantly influence use behaviour and behavioural intentions. Wei and Lim (2022) have

identified four distinct factors that have been linked in prior research to the adoption of smart agricultural technologies by farmers.

Subsequently, after applying UTAUT, further examination using UTAUT2 is carried out; UTAUT2 is another model developed by Venkatesh et al. (2012). After careful consideration, it is decided that additional constructs such as hedonic motivation, price value, and habit are inappropriate for this study at the current timeline; nonetheless, it has the potential for extended research in the future. Hedonic motivation is the enjoyment of technology application, regardless of the outcome (Khatimah et al., 2019; Schukat & Heisi, 2020). Nevertheless, price value pertains to the trade-off between a technology's advantages and its monetary price (Venkatesh et al., 2012). Moreover, farmers may need to experience whether the price change influences their behavioural intention. Then, a habit is described as the extent to which individuals behave spontaneously as a learning outcome (Venkatesh et al., 2012). These three concepts pertain to actual technology applications and are vital in evaluating technology acceptance and use behaviour. Moreover, the implementation of SFT in Sarawak still needs to improve, resulting in a limited understanding of this agricultural technique among farmers (Wee & Lim, 2022). Hence, the UTAUT2 theory and its supplementary constructs are insignificant in the present research study.

Additional evidence supports the UTAUT's superiority over alternative models, as demonstrated by empirical research in the past. This can be attributed to the reliability and consistency of its foundational constructs in predicting the intentions and perceived usefulness of system utilisations. An extensive validation of UTAUT was conducted over an extended period of time (Venkatesh et al., 2003). According to their findings, UTAUT explained approximately 70% of the variance observed in the intention to utilise technology and behaviour of individuals, and approximately 50% of the variance observed in their actual

utilisation of said technologies. Prior studies by Slade et al. (2015) and Abubakar and Ahmad (2013) have concentrated primarily on determining an individual's intention to employ a system prior to its implementation. As a result, the present inquiry finds this theory to be pertinent. Despite its limitations, UTAUT has acquired widespread practice, expansion, and integration in empirical research for implementing various information and communication technologies (Baishya & Harsh, 2020; Dwivedi et al., 2017). Furthermore, previous research has extensively employed UTAUT to explain the influencing factors on the behavioural intention of various technologies, including the acceptance of specific farming technologies (Li et al., 2020) and the implementation of blockchain in smart agriculture (Ullah, 2021). In a recent study, Wei and Lim (2022) examined the farmer's behavioural intention toward smart farming, then revealed that social influence emerged as the most influential factor in predicting behavioural intention. Similarly, von Veltheim et al. (2022) investigated the intention to use autonomous field robots to significantly impact PE, SI, EE, FC, and behavioural intention to embrace technologies in agriculture. Therefore, UTAUT can be an effective tool for evaluating the various aspects that influence farmers' adoption of SFT to sustain food security.

2.11 The Conceptual Framework

The UTAUT model is employed to identify the factors influencing the acceptance of farmers to adopt SFT, as well as the various factors that impact their acceptance to adopt SFT in sustaining food security in Sarawak. The conceptual framework comprises several independent variables: performance expectancy, social influence, effort expectancy, and facilitating conditions are the main determinants that influence the adoption of technology. These constructs known to positively affect the behavioural intention to adopt technology.

In addition, to being related to food security, these determinants are the known effect of the acceptance of farmers to adopt SFT in sustaining food security in Sarawak. Literature that has been reviewed in previous section also shed light on technology awareness as a moderator in relationship between performance expectancy, effort expectancy, social influence, facilitating conditions and the acceptance of farmers to adopt SFT. Additionally, technology awareness acts as a moderator between these independent variables and the acceptance to adopt SFT.

UTAUT has been widely utilized, extended, and integrated to facilitate the implementation of various ICT-based technologies for empirical research, notwithstanding its limitations (Baisha and Harsh 2020, Dwivedi et al. 2019). Furthermore, previous research has extensively employed UTAUT to elucidate the various aspects of technology acceptance, including but not limited to the following: the adoption of e-payment systems by university students (Salloum and Al-Emran 2018; Mohammad and Kasim 2018), the acceptance of technologies such as internet banking (Im, Hong, and Kang 2011), the adoption of peer-to-peer mobile payment by individual consumers (Al-Saedi et al. 2019; Patil et al. 2020), and the implementation of electronic finance services by financial institutions. An investigation into the implementation of e-government services in Malaysia was recently undertaken by Husin, Loghmani, and Zainal Abidin (2017), employing UTAUT as the foundational framework. Behavioural intention that contributes to IT acceptance is predicted by performance expectancy, effort expectancy, and social influence, according to the study. An additional finding of the study is that the adoption of e-government services can be predicted by facilitating conditions and behavioural intention. Therefore, by employing UTAUT, an optimal framework can be established to evaluate the

variables that influence of farmers to adopt SFT in sustaining food security. The following. Figure 2.2 illustrates the conceptual framework derived from the UTAUT model.

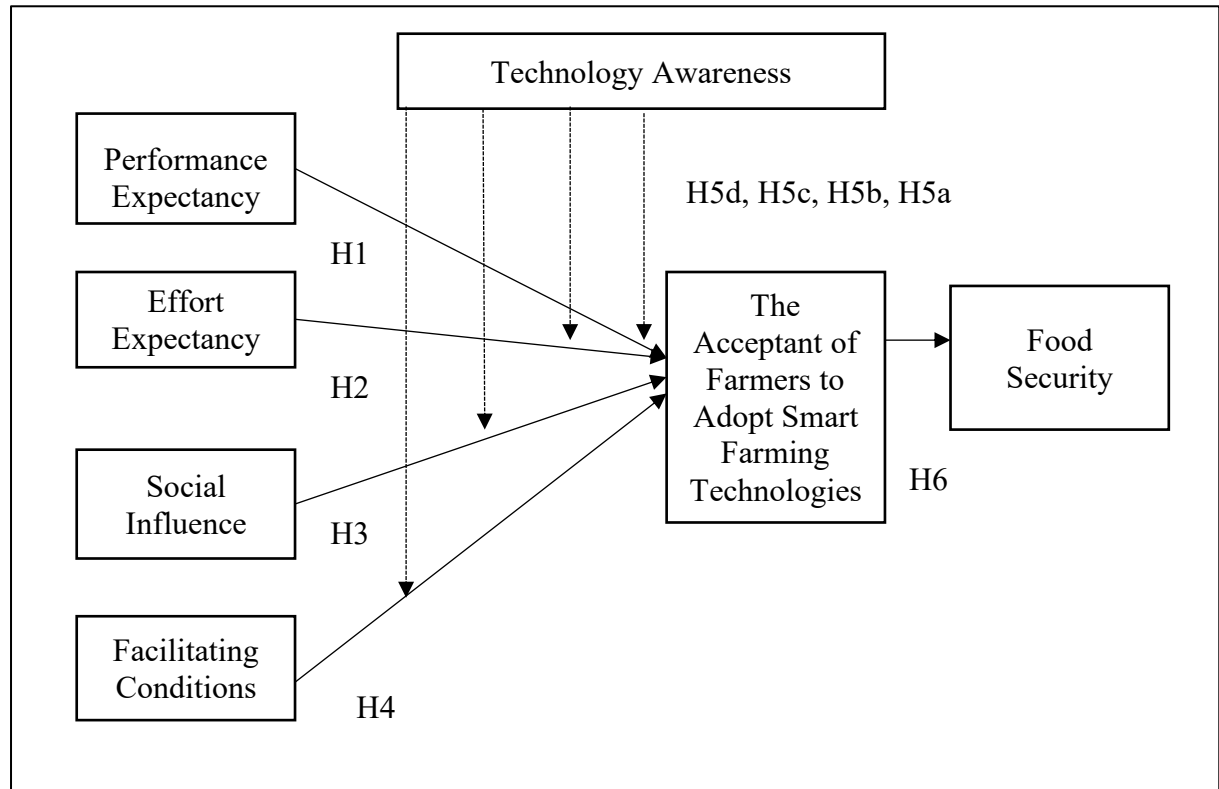


Figure 2. 2: Conceptual Framework

2.12 Development of Hypotheses

This part presents the formulation of nine hypotheses for the study. These hypotheses explore the potential associations among performance expectancy, social influence, effort expectancy, facilitating conditions, acceptance of farmers to adopt SFT, and moderating role of technology awareness. Finally, this study identifies the factors influencing the acceptance of farmers to adopt smart farming technologies in sustaining food security in the region of Sarawak.

2.12.1 Relationship between Performance Expectancy and the Acceptance of Farmers to Adopt SFT

PE refers to the extent to which technology offers consumers benefits in the execution of various activities or tasks (Venkatesh et al., 2003). The concepts of improved productivity and time efficacy have been consistently emphasised within the context of agriculture (Far & Rezaei-Moghaddam, 2017; Engotoit et al., 2016), alongside the concept of augmented profitability (Ronaghi & Forouharfar, 2020). PE plays a significant role in shaping German farmers' acceptance of the adoption of a crop protection smartphone application (Michels et al., 2020). PE is constructed by constituting three key components: relative advantage, outcome expectation, and perceived efficacy (Venkatesh et al., 2003). Therefore, the construct of PE can be likened to the variable of perceived usefulness within the TAM, which has gained significant popularity as a reliable, efficient, and succinct approach for forecasting technology adoption (Palau-Saumell et al., 2019). According to Engotoit et al. (2016), several research studies have broadened the definition to include the practice's contribution to managing agricultural systems. Incorporating general notions regarding the improvement of farm organisation (Duang-Ek-Anong et al., 2019) and the superiority or essentiality of the practice compared to its alternatives (Beza et al., 2018).

H1: Performance expectancy has a positive relationship towards the acceptance of farmers to adopt SFT.

2.12.2 Relationship between Effort Expectancy and the Acceptance of Farmers to Adopt SFT

EE is described as farmers' engagement in considering and evaluating the expected level of effort necessary for implementing smart farming technologies within the specific context of this study. Subsequently, an assessment is conducted to determine whether the

exertions align proportionally with the advantages derived from the utilisation of the technology. Moreover, previous studies concerning the adoption of mobile applications provided evidence to support the idea that effort expectancy impacts the intention to use. Additionally, a notable correlation exists between EE and behavioural intention (Thompson et al., 1991; Moore & Benbasat, 1991; Chao, 2019). Effort expectancy favours individuals' inclination to apply agricultural systems (Junadi & Sfenrianto, 2015). Similarly, EE has a constructive impact on German farmers' intention to employ smartphone-based crop protection (Michels et al., 2020). The utilisation of the application by farmers in this study is found to be influenced by the user-friendliness of the technology platform.

H2: Effort expectancy has a positive relationship towards the acceptance of farmers to adopt SFT.

2.12.3 Relationship between Social Influence and the Acceptance of Farmers to Adopt SFT

Agriculture is a multifaceted endeavour that encompasses both sociocultural and economic dimensions (Rasheed & Mahmod, 2018). The adoption of SFT by farmers can be motivated through social interactions and adherence to societal norms, which exert a significant amount of pressure. Within this study, SI is defined and measured through the involvement of faith-based organisations, community members, and peasant groups in persuading farmers to adopt smart agricultural practices. Hence, the societal impact on the adoption of SFT significantly influences farmers' acceptance of implementing them.

H3: Social influence has a positive relationship towards the acceptance of farmers to adopt SFT.

2.12.4 Relationship between Facilitating Conditions and the Acceptance of Farmers to Adopt SFT

Within the realm of technology adoption, FC has positive effects on individuals' acceptance to adopt information technology (Lakhal et al., 2013; Venkatesh et al., 2012; Jong & Wang, 2009; Venkatesh et al., 2003; Moore & Benbasat, 1991). Individuals must possess specific skills in configuring and operating computer systems and establishing Internet connections to use Internet banking services (Martins et al., 2014; Rahi et al., 2018). According to Putri (2018), FC has an encouraging impact on adopting electronic payment methods. A study on SFT provided evidence of a relationship between facilitating conditions and the behavioural intentions of farmers (Ronaghi & Forouharfar, 2020; Nejadrezaei et al., 2018; Li et al., 2020).

H4: Facilitating conditions has a positive relationship towards the acceptance of farmers to adopt SFT.

2.12.5 Moderating Role of Technology Awareness.

Fewer studies involve technology awareness as a moderator on the association between behavioural intention and use behaviour; this bond is moderated by technology awareness (Abubakar & Ahmad, 2013; Omar, 2011). In addition, consciousness is a vital criterion for the establishment and progression of ethical principles (Lip-Sam & Hock-Eam, 2011). The significance test for the observed relationships between the model's constructive variables and the technology awareness variable produced statistically significant results (Daniali et al., 2022). In this study, the researchers' hypotheses are limited empirically tested, particularly regarding the role of technology awareness as the moderator in the associations between UTAUT constructive factors and behavioural intention. This study investigates the

impact of technology awareness in moderating the correlations between PE, SI, EE, and FC, and the acceptance of farmers to adopt SFT.

H5a: Technology awareness moderates a positive relationship between performance expectancy and the acceptance of farmers to adopt SFT.

H5b: Technology awareness moderates a positive relationship between effort expectancy and the acceptance of farmers to adopt SFT.

H5c: Technology awareness moderates a positive relationship between social influence and the acceptance of farmers to adopt SFT.

H5d: Technology awareness moderates a positive relationship between facilitating conditions and the acceptance of farmers to adopt SFT.

2.12.6 Relationship between the Acceptance of Farmers to Adopt SFT and Sustaining Food Security

Technology acceptance is contingent on several variables, including the technology's economic viability, national policies, and the legal environment that results from these policies. Mutungi et al. (2023) examine the effect of the acceptance of technologies in farming activities as significant. Ahmed et al. (2018) conducted a study that shows that implementing IoT technology can enhance food production and facilitate food provision to individuals. One potential advantage that may arise from the adoption of a novel technology is the ability of farmers to generate profits (Wu, 2022). It has been discovered that farmers who adopt technological advancements can contribute to the enhancement of crop productivity and the ability to expect variations in their yields. According to Elijah et al. (2018), the adoption of IoT-A by farmers resulted in several benefits, including improved product quality, increased productivity, and enhanced profitability in agriculture. Based on the findings and consistency observed in the studies as mentioned earlier, it can be deduced

that there is a positive correlation between the acceptance of farmers to embrace smart farming technologies and the ability to maintain food security.

H6: The acceptance of farmers to adopt SFT has a positive relationship towards sustaining food security in Sarawak.

2.13 Summary of Hypotheses Development

The following are summarising of the hypotheses development mentioned above to achieve the objectives of the study:

H1: Performance expectancy has a positive relationship towards the acceptance of farmers to adopt SFT.

H2: Effort expectancy has a positive relationship towards the acceptance of farmers to adopt SFT.

H3: Social influence has a positive relationship towards the acceptance of farmers to adopt SFT.

H4: Facilitating conditions has a positive relationship towards the acceptance of farmers to adopt SFT.

H5a: Technology awareness moderates a positive relationship between performance expectancy and the acceptance of farmers to adopt SFT.

H5b: Technology awareness moderates a positive relationship between effort expectancy and the acceptance of farmers to adopt SFT.

H5c: Technology awareness moderates a positive relationship between social influence and the acceptance of farmers to adopt SFT.

H5d: Technology awareness moderates a positive relationship between facilitating conditions and the acceptance of farmers to adopt SFT.

H6: The acceptance of farmers to adopt SFT has a positive relationship towards sustaining food security in Sarawak.

2.14 Summary

The dependent, independent, and moderator variables that were employed in the current investigation are detailed in this chapter. Utilisation of the Unified Theory of Acceptance and Use of Technology (UTAUT) further elucidates the fundamental theories that were employed to establish the connections between effort expectancy, performance expectancy, social influence, facilitating conditions, technology awareness, the acceptance of farmers to adopt SFT, and food security. Additionally, the conceptual framework and the hypotheses development are elaborated upon in this chapter. Concerning the aforementioned variables pertaining to farmers' adoption of SFT as a means of ensuring food security and accomplishing the stated objectives of this study, the methods employed to carry out the current investigation are elucidated upon in detail in the subsequent chapter on research methodology.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter is related to a complex structured approach employed to investigate and explore various aspects of the surrounding world systematically and scientifically. The chapter commences by offering a summary of the existing research designs, subsequently delving into a detailed description of the research design applied in this research. The founded research design includes the interpretation of the target population, data collection method, operationalisation of construct and measures, questionnaire design, pre-testing and pilot study, validity and reliability, descriptive analysis, PLS-SEM, research objectives and lastly recommendation and conclusion. Research objectives typically come before the methodology section in the research design. They are presented early in the research proposal or plan to provide a clear outline of what the study aims to achieve. In addition, placing the objectives after the results can emphasise the alignment between what was aimed for and what was found and provide a clear narrative on how each objective was met or addressed by the findings. The concluding sections of this chapter delineate the data analysis techniques used in this research study. The research design flowchart is shown in Figure 3.1.

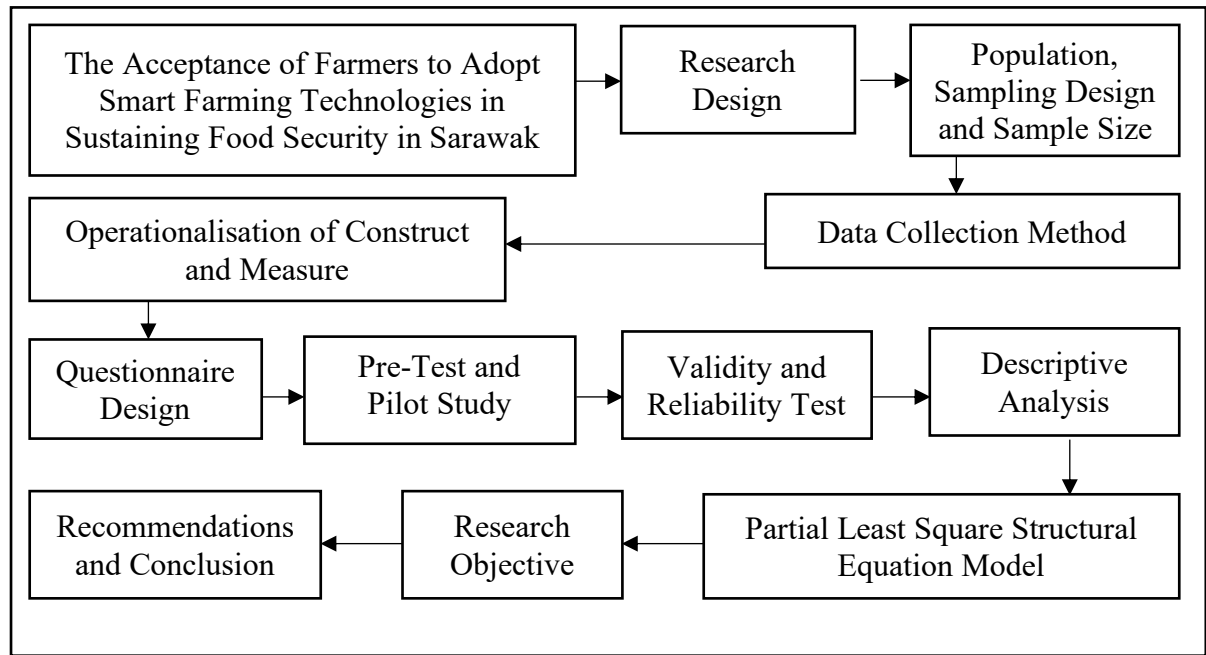


Figure 3. 1: Research Design Flowchart
Source: Adopted from Jilcha Sileyew (2020)

3.2 Research Design, Sample, and Procedure

To generalize across farmers residing in Sarawak, the population of the present study consists of farmers who are currently living and have been living in Sarawak for more than a year. Sekaran (2000) noted that a sample size of between 30 to 500 samples would be sufficient for most studies. As the aim of this study is to identify the factors influencing the acceptance of farmers to adopt smart farming technologies in sustaining food security in Sarawak, data were collected through online survey questionnaires and face-to-face with the local farmers. The current study adopts a quantitative approach as its primary focus and causal research to identify the cause-and-effect relationship between two variables. Consequently, a quantitative study design may be employed to conduct a cross-sectional deductive investigation.

In this study, two crops were selected: vegetables and fruits because they are essential to crop production in Sarawak obtained from the Department of Agriculture Malaysia (2022) by using purposive or judgmental sampling. This sampling is a non-probability sampling technique that establishes the parameters of comprehension and proceeds to locate subjects who, by their knowledge or experience, were able and willing to contribute the necessary data (Etikan et al., 2016). There were 76,732 farmers who produced vegetables and fruits in Sarawak (Department of Agriculture Malaysia, 2022). For this study, the researcher collected data from farmers who are residing in Sarawak and produced vegetables and fruits. This study was limited to the farmers listed under agriculture crop subsidy in Kuching, Sarikei, Samarahan, Serian, and Kapit to get sufficient data. Moreover, these divisions yield high production of vegetables and fruits (Department of Agriculture Malaysia, 2022).

In addition, the researcher employed G*Power 3.1 to determine the sample size of this study. Power analysis was utilised in order to determine the optimal sample size for the present investigation. This is the consequence of recent advancements, as indicated by Hair et al. (2017), Hair et al. (2018), Hair et al. (2019), Kline (2016), Ringle et al. (2018), and Uttley (2019). The number of predictors utilised in this study was determined by the nine hypotheses that were constrained. Four predictors comprise the maximum number of arrows pointing to dependent variables in the model, which corresponds to the number of predictors. The test family selected for this investigation consists of linear multiple regression with fixed model R² deviation for a statistical test, followed by F test analysis. Compute the required sample size, power, and effect size for a particular type of power analysis, as a prior. The findings revealed a power value of 0.95 and an effect size of 0.15, both of which were considered moderate. The error probability of 0.05 is associated with a reduced likelihood of perpetrating a Type II error (Cohen, 1988; Hair et al., 2017; Kang, 2021; Uttley, 2019).

In social science research, a threshold of 80 percent or greater is generally regarded as an acceptable level of statistical power (Cohen, 1988; Hair et al., 2017; Uttley, 2019). Based on the analysis done, it was concluded that a minimum sample size of 129 samples was necessary to conduct Partial Least Squares (PLS) in this study. However, this study aimed for a higher sample response rate in order to provide a more solid result at a sample size of 300 respondents. The G*Power calculation on the sample size of this study is in Figure 3.2.

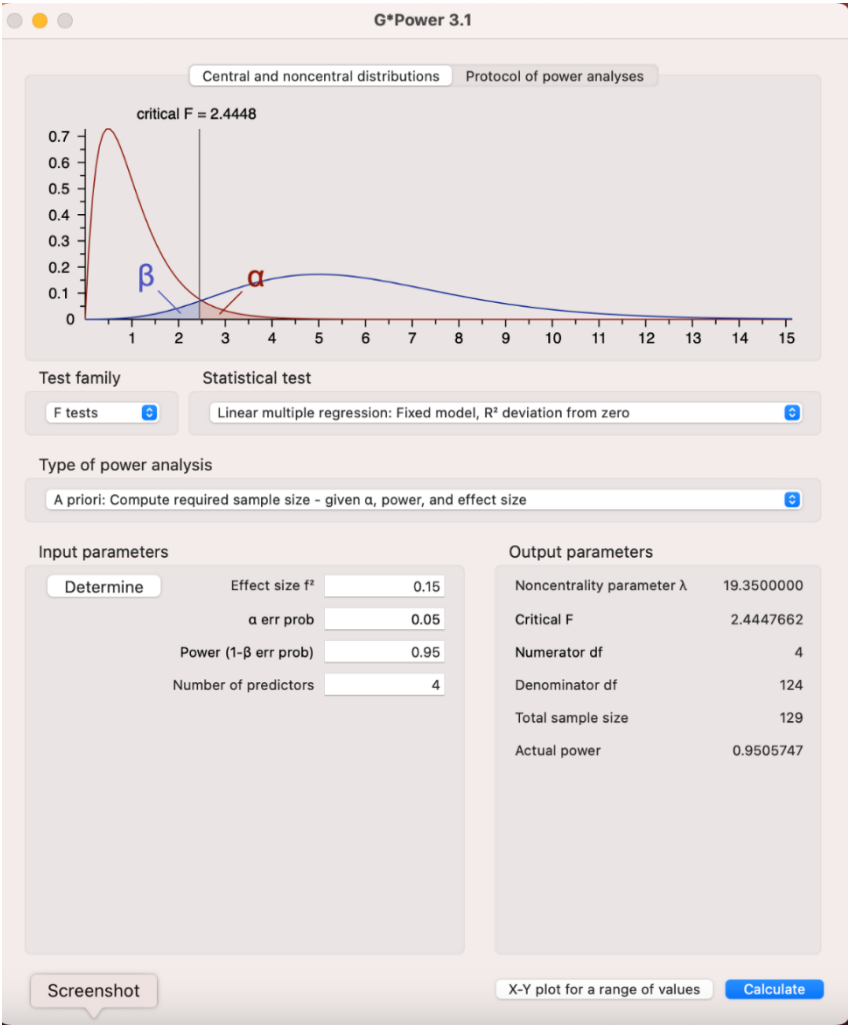


Figure 3. 2: G*Power Calculation

3.2.1 Characteristics of Farmers

Farmers are recognised as the main actors with direct involvement in agriculture productivity. This study includes active farmers residing in Sarawak. Thus, they have significant roles in sustaining food security. In addition, individual farmers' decision-making processes enable the examination and formulation of favourable and unfavourable opinions regarding agricultural practices and novel technologies (Saidah et al., 2020). In addition, this study selected the farmers who cultivated two vegetables and fruits because they are essential to crop production in Sarawak, which can provide nutrition, job opportunities and generate income for farmers (Dardak et al., 2022). Furthermore, the study was limited to the farmers listed under agriculture crop subsidy from the Department of Agriculture Sarawak.

3.3 Unit of Analysis

The determination of the unit of analysis pertains to whether the sample under investigation is of an individual, dyadic, group, organisational, or culture-specific nature. The reason for this is the degree of data aggregation that occurs during the data analysis phase (Sekaran & Bougie, 2013; Zikmund et al., 2013). As mentioned previously, the present study tends to examine farmers in terms of farmers' decision-making processes enable the examination and formulation of favourable and unfavourable opinions regarding agricultural practices and novel technologies (Saidah et al., 2020). Therefore, the unit of analysis in this study was individual, for instance, farmers.

3.4 Data Collection Method

Initially, the researcher employed the quantitative method to collect data for this study. The researcher distributed and collected the data via face-to-face and online surveys from farmers in Sarawak to test the research model and to achieve the research objectives. By utilising self-administered questionnaires, the study's subjects can peruse the questionnaire and obtain all pertinent information regarding its completion from the researcher (Zikmund et al., 2013).

Data collection began on September 12th, 2023 until October 14th, 2023. The procedure started with a list of names of farmers in agriculture crop subsidies. It was randomly selected by the representative area staff from the Department of Agriculture, taking into account various demographic and geographical parameters. This approach was undertaken to mitigate any potential selection bias and enhance the generalizability of the study findings. Then, the researcher was invited by the Department of Agriculture to join the program during dialogue sessions with villagers and verification of the farmer programs. The researcher together with representative agricultural area staff distributed physical questionnaires to the respondents and clarified any questions they had. Before distributing the questionnaires, the researcher sought confirmation from the respondents that they met the requirements such as farmers residing in Sarawak and planting vegetables and fruits to participate in the study. This was to ensure that the samples were valid and reliable. After that, the researcher explained the objective of the study and detailed instructions were given to the respondents to ensure they understood the survey questionnaires and then provided accurate answers. On the other hand, the more educated farmers could answer the questionnaires by themselves, however, for those with no formal education the researcher

explained the meaning of the questions to obtain the answers from them. Lastly, the researcher collected the answers from the targeted respondents.

In addition, the questionnaires were also distributed through an online survey (Google Form survey through WhatsApp). A recent scholarly inquiry by William et al. (2022) concurred that online questionnaires are employed to examine the factors that impact farmers' choices in adopting innovative agricultural technologies. For online questionnaires, the researcher approached the representative agricultural area staff of the Department of Agriculture from other Sarawak divisions to distribute the online survey through Whatsapp. There were several screening questions before completing the questionnaires such as “Are you a farmer residing in Sarawak?”. Respondents who answered “No” to the screening question were excluded from the sample. However, if the respondents responded “Yes,” they could proceed to another screening question, “Types of crops.” If the respondents answered “Vegetables” or “Fruits,” they were considered as well-qualified sample for further study. According to Malhotra (2010), internet sampling and surveys offer many advantages. The respondents can fill out the survey at their convenience. Furthermore, using Google Forms as an internet survey can integrate intelligent features such as automated skip patterns, dividing indicators into each section, being user-friendly, instantly exporting the data into an Excel sheet, and other beneficial features.

Furthermore, the respondents were assured that their answers were meant for research purposes, would not be seen by anyone, and would not be given to third parties. The respondents were asked to answer the questions based on their experience and knowledge on agriculture activities. A total number of 300 sets of questionnaires were distributed personally and through representative area staff to the respondents, only 280

(93.33%) were returned. Out of 280 returned physical questionnaires, only 247 physical questionnaires were usable for analysis. To ensure the data were valid and reliable for this study, 33 answered questionnaires were discarded due to missing data and unanswered questions. Additionally, the questionnaires were distributed through Google Forms via WhatsApp, which gained 92 respondents. To confirm the data were valid and reliable, 9 returned online questionnaires were discarded because the respondents were not qualified to proceed to answer the questions at the preliminary questions stage, and as a result, 83 data were usable for analysis. Therefore, the total number of respondents in this study is 330.

3.5 Operationalisation of Constructs and Measure

Operationalisation refers to translating research concepts into measurable variables of interest (Bell & Bryman, 2018). The objective is to utilise questionnaires as a means of eliciting responses from participants. The operationalisation of theoretical constructs is employed by processing multi-item scales that are previously validated and adapted from a prior study; the surveys are also designed to incorporate items that effectively evaluate the relevant variables. It is imperative to acknowledge that during the process of rephrasing the items, meticulous attention is given to ensure that the resultant questions closely resemble the original form.

The UTAUT variables are assessed using a 7-point Likert scale; on each item, the respondents indicate their level of agreement or disagreement. The scale points range from (1) to (7), respectively, from ‘strongly disagree’ to ‘strongly agree.’ The efficacy of data collection can be enhanced through the implementation of strategies aimed at increasing response rates, shortening completion time, and reducing response dropout rates (Desai &

Reimers, 2019). A 7-point Likert scale offers a broader range of choices, enhancing the probability of attaining individuals' desired state of reality. Furthermore, the utilisation of this tool aids in the examination of the gathered data by researchers due to its normative nature and ease of administration, thereby enabling enhanced reliability and validity of findings during subsequent stages of the study process (Taherdoost, 2019; Hair et al., 2020). The extant body of literature also argues, within a specific context, that attitudes tend to form clusters. Based on the observed reliability of survey participants' answers, it is probable that a 7-point Likert scale may exhibit superior performance compared to a 5-point Likert scale, given the specific selection of scale items in the survey construct. Table 3.1 presents a concise overview of the measurement of the construct.

Table 3. 1: Summary of the Measurement of the Construct

Construct	Sources	Measures	Scale
PE	Venkatesh et al. (2003), Shiferaw and Mehari (2019), Ronaghi and Forouharfar (2020), Schukat & Heisi (2021), Self-developed	PE1: Using the smart farming technologies will useful in doing my farm activities. PE2: Using the smart farming technologies will help me to accomplish my tasks more quickly than before in the farm. PE3: Using the smart farming technologies will increase my chances of achieving higher crop productivity. PE4: Using smart farming technologies will increase my chances of increasing my income. PE5: Using smart farming technologies will reduce the use of fertilisers, pesticides, and labour costs.	Likert Scale 1(Strongly disagree) – 7 (Strongly agree)
EE	Venkatesh et al. (2003), Becker (2016) , Braun (2013), Ronaghi & Forouharfar (2020),	EE1: Learning how to use the smart farming technologies is easy for me. EE2: My first impression of the smart farming technologies	Likert Scale 1(Strongly disagree) – 7 (Strongly agree)

	Schukat & Heisi (2021), Self-developed	could be described as clear, favourable and comprehensive. EE3: I would find the smart farming technologies easy to use. EE4: It is applicable to me become a skilful and deft user of the smart farming technologies. EE5: It would be easy for me to operate smart farming technologies.	
SI	Venkatesh et al. (2003), Chiu & Tsai (2016), Rasme et al. (2018), Ronaghi & Forouharfar (2020), Schukat and Heisi (2021), Self-developed	SI1: The people who are important to me think that I should use the smart farming technologies. SI2: The people who have influence on my behaviour, think that I should use the smart farming technologies. SI3: The people whose opinions are valuable to me prefer to use smart farming technologies. SI4: My near relatives, friends, and acquaintances are using the smart farming technologies themselves. SI: The social media platform influence me to use smart farming technologies.	Likert Scale 1(Strongly disagree) – 7 (Strongly agree)
FC	Venkatesh et al.,(2003), Bhattacharjee & Hikmet (2008), Ronaghi and Forouharfar (2020), Shuckat & Heisi (2021), Self-developed	FC1: I have necessary facilities for using smart farming technologies relevant to farming. FC2: I have a basic knowledge on how to use smart farming technologies. FC3: I can get help from others when I have difficulties using smart farming technologies. FC4: The internet access is available on the whole farm area. F55: The smart farming technologies are more compatible compared to traditional farming.	Likert Scale 1(Strongly disagree) – 7 (Strongly agree)
AW	Alaeddin and Altounjy (2018),	AW1: I follow the news about the smart farming technologies	Likert Scale

	Self-developed	AW2: I follow the developments of the smart farming technologies. AW3: I discuss with friends and people around me issues of smart farming technologies usage. AW4: I read about the problems of smart farming technologies usage. AW5: I aware on the advantage of smart farming technologies.	1(Strongly disagree) – 7 (Strongly agree)
AC	Saad & Salman (2021), Self-developed	AC1:I will accept smart farming technologies if it cheap and profitable. AC2: I will accept if spare parts of smart farming technologies should be easy to obtain. AC3: If crops yields can increase, I have no hesitation in accepting smart farming technologies. AC4: The introduction of smart farming technologies should be able to increase my income. AC5: I will accept smart farming technologies if it can reduce production cost.	Likert Scale 1(Strongly disagree) – 7 (Strongly agree)
FS	Ali et al., (2018), Yina (2014), Hayat (2021)	FS1: I believe smart farming technologies adoption may help to increase the crop yield. FS2: I believe smart farming technologies adoption may help to increase my farm's income. FS3: I believe smart farming technologies adoption may help to improve farm capacity utilisation. FS4: I believe that smart farming technologies adoption may help to improve the efficiency of the farm. FS5: I believe that smart farming technologies adoption may help to increase the farm's profitability.	Likert Scale 1(Strongly disagree) – 7 (Strongly agree)

Demographic	Age, Ethnic, Marital Status, Ordinal Monthly Income, Education Level, Year of Farming Experience.
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3.5.1 Performance Expectancy

PE pertains to the perceived advantages a user envisions when utilising a technology to accomplish a specific task (Venkatesh et al., 2003). Ronaghi and Forouharfar (2020) conducted measurements to assess the extent of performance improvement, labour savings, profitability, and benefits associated with the implementation of smart agricultural technologies. The study objective is to ascertain the degree of enhancement in performance resulting from these technologies. Consequently, this study evaluated the impact of SFT on farmers' comfort and utility to assess the effectiveness of these technologies in the field of smart agriculture. Five items were utilised to evaluate the performance expectancy, four items were adapted from Venkatesh et al. (2003), Shiferaw and Mehari (2019), Ronaghi and Forouharfar (2020), Schukat and Heisi (2021) with one self-developed item.

3.5.2 Effort Expectancy

EE pertains to the user's insight regarding the user-friendliness and intricacy of the system, according to Venkatesh et al. (2003). The evaluation of measure EE is contingent upon the extent to which information systems exhibit simplicity in terms of usability, interaction, and learnability (Ronaghi & Forouharfar, 2020; Schukat & Heisi, 2020). Four elements within the domain of environmental engineering are also employed to demonstrate proficiency in the utilisation of intelligent agricultural technologies, particularly in relation to their increased adoption rate. Given that previous studies have already explored the variable of interest, it is considered appropriate for the present inquiry. For this study, five items were utilised to evaluate the EE, four items were adapted from Venkatesh et al. (2003),

Becker (2016), Braun (2013), Ronaghi & Forouharfar (2020), Schukat & Heisi (2021) with one self-developed item.

3.5.3 Social Influence

According to Venkatesh et al. (2003), SI is defined as the extent to which an individual's decision-making process is influenced by the suggestions and expectations of others regarding the use of a particular system. In the study by Chiu and Tsai (2014), SI is assessed by investigating the anticipated influence of significant individuals, relatives, and friends on users, including an assessment of the level of support provided by studying and working settings to examine the impact of social standpoints. In a recent study conducted by Ronaghi and Forouharfar (2020), the findings show that social influence has a noteworthy and optimistic effect on farmers' intention to accept and apply technology in their agricultural activities. For this study, five items were utilised to evaluate the SI; four items were adapted from Venkatesh et al. (2003), Chiu & Tsai (2016), Rasmi et al. (2018), Ronaghi & Forouharfar (2020), Schukat & Heisi (2021) with one self-developed item.

3.5.4 Facilitating Conditions

Venkatesh et al. (2003) defined FC as the requisite capacity and resources necessary to utilise a given system effectively. Previous research conducted by Bhattacharjee and Hikmet (2008), as well as Ronaghi and Forouharfar (2020) examined the measurement of facilitating conditions about its impact on the living and working environment, system viability, assistance accessibility, and the provision of compulsory knowledge and resources for effective practical application. The central concept of this variable posits that agriculturists possess the requisite resources to utilise smart farming technologies. In this study, five items were used to evaluate the FC; four items were adapted from Venkatesh et

al. (2003), Bhattacharjee & Hikmet (2008), Ronaghi & Forouharfar (2020), Shukat & Heisi (2021) with one self-developed item.

3.5.5 The Acceptance of Farmers to Adopt Smart Farming Technologies

The level of acceptance of a novel technology among farmers is primarily indicated by their BI to utilise it (Schukat et al., 2019; Ambong & Paulino, 2020). The concept of BI can be understood as the personal perception of the probability that an individual will partake in a particular behaviour, as Venkatesh et al. (2003) described. The measurement of business intelligence is determined by factors such as intention, prediction, and intended use (Macedo, 2017). In this study, these factors were incorporated into the framework of strategic foresight and SFT in the current research. The utilisation in question can be characterised through the lens of BI. Based on the findings of Michels et al. (2020) and Schukat and Heisi (2021), a significant correlation exists between BI and the subsequent actual use of a particular system or technology. In this study, five items were utilised to evaluate farmers' acceptance; four were adapted from Saad and Salman (2021) with one self-developed item.

3.5.6 Technology Awareness

Technology awareness plays a significant role in determining the acceptance behaviour of farmers, particularly in terms of their familiarity with a specific technology (Kamarul Zaman et al., 2023). In other words, it pertains to the user's awareness and knowledge. For this study, five items were utilised to evaluate the awareness; four items were adapted from Alaeddin and Altounjy (2018), with one self-developed item.

3.5.7 Food Security

Food security is defined as consistent and accessible physical access and socio-economic viability to obtain nutritious and safe food that meets their dietary needs and choices, promoting a dynamic, healthy lifestyle (FAO, 1996). The adoption of SFT in

sustaining food security can increase the production yield and enhance farm financial performance (FAO, 2018). For this study, five items were utilised to evaluate the food security; all adapted from Ali et al. (2018), Yina (2014), and Hayat (2021).

3.6 Questionnaires Design

The survey instrument developed in the research covered four double-sided pages and a close-ended question. The assessment consisted of 35 questions, repositioned into four distinct sections. Section 1 explicitly encompasses the independent variables: performance expectancy, effort expectancy, facilitating conditions, and social influence. Section 2 explored the moderating role of technology awareness, while Sections 3 and 4 examined the acceptance of farmers to adopt smart farming technologies and food security. The participant information statement and preliminary questions were delivered in the early part of the questionnaires to apprise respondents of the questionnaire's objectives, emphasise the voluntary nature of their participation, and assure them of the strict confidentiality measures for the collected data (Dillman et al., 2014).

Through questionnaire distribution to academicians and experts in the fields matter for validation, feedback were solicited regarding the pertinence of each item to the purpose of the questionnaires. The academicians and experts evaluated the items using a five-point scale: 1 = poor, 2 = fair, 3 = good, 4 = very good, and 5 = excellent, as per the established definition of research impact that facilitates a further investigation. As defined by Molas-Gallart et al. (2016), research impact pertains to the complex and multifaceted pathways that connect science, practice, and outcomes. For the purpose of this research, academicians and experts were additionally requested to assess whether the items adequately addressed the crucial elements or lacked specific components. Additionally, they were permitted to insert

remarks regarding any item. They were contacted by the researchers via email. The experts and academicians were duly apprised of the study's aims and provided with the assurance that the data would be handled in strict confidence.

Furthermore, to ensure a clear and understandable understanding of the questionnaire, it was translated into Bahasa Malaysia. This decision is based on the fact that almost all farmers in this study were fluent in the local language, Bahasa Malaysia. A second individual, to mitigate any potential misinterpretation of the original intent of the questions, conducts a cross-reference review of the Bahasa Malaysia version. Besides, to alleviate the presence of implicit assumptions and enhance the ease of questionnaire completion, straightforward language was employed (Creswell, 2014). The utilisation of back-translation for questionnaire translation may yield accurate translations. Still, there needs assurance in generating precise words with the intended meaning and obtaining consistent responses globally. Conversion of the survey can be carried out in two different ways: the expert team approach and the committee approach (Douglas & Craig, 2007). Irrespective of the method engaged in forming the ultimate translation, it is advisable to follow a sequence of five distinct phases: translation, review, adjudication, pre-testing, and documentation (Harkness, 2003). In the present study, the expert team method was utilised. Before examining the questionnaire's original meaning, the researcher and translator translated it into the local language.

3.7 Pre-testing

Pre-testing is a crucial process carried out before the actual data collection. The sample collected and the final model analysis must be identical. Pre-testing the survey questionnaire ensures that respondents understand the questions and that there are no

problems with the content (Sekaran & Bougie, 2016; Stockemer, 2019). Pre-testing the survey questionnaire will enable a researcher to refine the survey to eliminate analytical errors.

Farmers and agriculture experts, as well as crop professional cultivators, are contacted to acquire feedback on the context of the questionnaire's reliability and understanding of the local context through a pre-test. Consequently, the participants perceived the translated questionnaire version as comprehensible and the study context appropriate.

3.8 Pilot Study

A pilot study can be well-defined as a preliminary exploration directed to replicate the data-gathering processes employed in the primary research. Van Teijlingen and Hundley (2002) outlined multiple objectives for implementing a pilot study. These objectives include evaluating the suitability of study methodologies, assessing the viability of a large-scale project, establishing the practicality and feasibility of the research protocol, identifying logistical challenges, gathering preliminary data, evaluating the effectiveness of the sampling target and technique, ascertaining the appropriate sample size, as well as persuading finance bodies of the feasibility and value of the main study, among others. A preliminary study is conducted before gathering data to evaluate the internal consistency of the survey instruments and ensure that they are clear and relevant within the given context. In this context, the applicable sample size for the pilot study can be determined via several principles; Cooper and Schindler (2011) proposed that a sample size of between 25 and 100 entities is recommended. However, it is commonly acknowledged that, in general, for conducting a pilot study, a sample size in the range of 10 to 30 contributors is deemed

adequate (Hill, 1998; Isaac & Michael, 1995). Furthermore, certain scholars recommend that the sample size for the primary analysis should ideally comprise 10 percent of the total sample (Connelly, 2008).

However, earlier research in the agriculture and finance domains typically utilised a sample size of 30 individuals for the pilot study, such as the implementation of smart farming technologies (Jaroenwanit et al., 2023). For this task, the researcher managed to get 40 respondents to answer this study's pilot test. Data collection for the pilot study commenced on July 12th, 2023, and concluded on July 15th, 2023, spanning four days. The questionnaires were disseminated to the farmers via the messaging application WhatsApp. Before responding to the survey questionnaire, the farmers were provided with a concise overview of smart farming technologies to familiarise them with the application. After completing the preliminary test, no modifications were made to any questionnaire, as it was found that the farmers comprehended the inquiries effectively. A validity and reliability test using Statistical Package for the Social Sciences (SPSS) version 29 software is carried out using the data collection from the preliminary test. Sekaran and Bougie (2013) stated that the assessment of the internal consistency of measured items conducted with Cronbach's alpha at a threshold of 0.70 is satisfactory. According to Hinton et al. (2004), a moderate level of reliability is indicated at a value between 0.5 to 0.7, whereas a high level of reliability is indicated at a value between 0.7 and 0.9. Meanwhile, Hair et al. (2016) emphasised the significance of interpreting the reliability analysis results based on the magnitude of the coefficient, as outlined by the Rule of Thumb: coefficients below 0.6 are considered poor, ranging from 0.6 to less than 0.7 are considered moderate, ranging from 0.7 to less than 0.8 are considered good, ranging from 0.8 to less than 0.9 are considered very good, and 0.9 and above are considered excellent. Therefore, based on the Cronbach's alpha obtained for each

construct, it can be concluded that the questionnaire items are deemed reliable, as indicated in the table provided.

Table 3. 2: Validity and Reliability Result

Variable		No.of items	Loading Factor	Cronbach's Alpha
Performance Expectancy	PE1	5	0.814	0.828
	PE2		0.800	
	PE3		0.753	
	PE4		0.715	
	PE5		0.764	
Effort Expectancy	EE1	5	0.724	0.878
	EE2		0.690	
	EE5		0.919	
	EE4		0.843	
	EE5		0.891	
Social Influence	SI1	5	0.853	0.802
	SI2		0.861	
	SI3		0.581	
	SI4		0.661	
	SI5		0.752	
Facilitating Conditions	FC1	5	0.738	0.806
	FC2		0.833	
	FC3		0.615	
	FC4		0.723	
	FC5		0.807	
Technology Awareness	AW1	5	0.896	0.927
	AW2		0.954	
	AW3		0.775	
	AW4		0.872	
	AW5		0.905	
The Acceptance of Farmers to Adopt SFT	AC1	5	0.600	0.852
	AC2		0.884	
	AC3		0.877	
	AC4		0.759	
	AC5		0.836	
Food Security	FS1	5	0.642	0.834
	FS2		0.851	
	FS3		0.789	
	FS4		0.741	
	FS5		0.822	

3.9 Techniques for Data Analysis

The present study utilised Smart-PLS 4.0 and Statistical Package for Social Science (SPSS) 29.0 for subsequent analysis. It is advisable to employ a variance-based structural equation modelling (SEM) method, specifically Partial Least Squares structural equation modelling (PLS-SEM), in order to analyse the hypotheses. This methodology is highly suitable for assessing the predictive associations between various precursors and their respective outcomes (Hair et al., 2022; Sharma et al., 2018). As a result, this methodology enables the integration of latent constructs, which are evaluated via observable indicators or variables, thus improving the reliability and accuracy of data analysis (Hair et al., 2011). Non-response errors are a prevalent challenge in data collection within quantitative research techniques (Queirós et al., 2017). Ensuring the completeness and adherence to the study requirements of the collected data becomes of utmost importance. Therefore, for this study, the initial data analysis phase involved examining and refining the gathered data for utilisation. This process involved analysing the data obtained from the statistical results provided by Google Forms and WhatsApp after filtering the quality and rate of response; thus, to ensure a fair representation of respondents, data was manually examined, supporting the subsequent decision-making process regarding the hypotheses.

3.9.1 Descriptive Analysis

The descriptive analysis for the instrument items is tested by using SPSS 29.0 software system to obtain the descriptive statistics, specifically the frequency, central tendency, and dispersion or variation; in addition to investigate the relationship of interest (Kaliyadan & Kulkarni, 2019; Mishra et al., 2019). This study included data analysis by examining the frequency and significance of specific attributes of factors. Frequency is calculated by dividing total occurrence counts by entire component counts within a particular

group (Puteh & Azman Ong, 2017; Kaur et al., 2018). In this study, the frequency variable pertained to the demographic profiles of the respondents, which served as determinants for each individual's profile (Mishra et al., 2019). The mean score was employed to identify the independent and dependent variables. Similarly, this study deployed a descriptive analysis of multiple variables pertaining to performance expectancy, effort expectancy, social influence, facilitating conditions, technology awareness, the acceptance of farmers to adopt SFT, and food security.

3.9.2 Common Method Variance

According to Podsakoff et al (2003), common method variance (CMV) is variance attributable to the measurement method rather than the constructs that the measures represent. In other words, CMV introduces the possibility of common method bias by producing illusory internal consistency. Type I error (false positive) and Type II error (false negative) may result from the inflation or deflation of the observed relationships between constructs due to measurement errors. A type I error arises when a researcher rejects a null hypothesis that is, in fact, true in the population, while a type II error arises when the researcher fails to reject a null hypothesis that is, in fact, false in the population. Therefore, Harman's single-factor test is frequently employed as a statistical method to determine whether the majority of the variability in the data can be ascribed to a single factor (Chang et al., 2010). Winkelbach and Walter (2015) proposed that common method variance is associated with a factor that accounts for over 50 percent of the variance. As a consequence, this study employed Harman's single-factor analysis to identify and regulate potential CMV.

3.9.3 Structural Equation Modelling

Structural Equation Modelling (SEM) is a multivariate data analysis technique of the second generation that is frequently employed to validate the linear and additive causal

models that have theoretical support (Haenlein & Kaplan, 2004). SEM facilitates the investigation of intricate research issues by quantifying latent variables that are difficult to observe and quantify. Furthermore, SEM has garnered recognition as the statistical framework that elucidates the interconnections between numerous variables. According to the findings of Gerbing and Anderson (1988), structural equation modelling (SEM) allows scientists to address a collection of interconnected research inquiries through a unified, methodical, and all-encompassing examination of the direct and indirect connections between numerous independent and dependent constructs. Moreover, Hair, Black, Babin, and Anderson (2010) observed that SEM is a hybrid approach incorporating dependent and interdependent techniques. This is primarily due to the fact that SEM is built upon multivariate techniques, namely factor analysis and multiple regression analysis. Conversely, SEM comprises an inner and exterior submodel. The outer model delineates the associations between latent variables and their observed indicators, while the internal model delineates the correlations between independent and dependent variables (Wong, 2013).

Furthermore, SEM distinguishes between exogenous and endogenous variables. Latent and multi-item equivalents of independent variables are exogenous variables. Conversely, endogenous variables are latent and consist of dependent variables matched across multiple items (Hair et al., 2010). In addition, Wong (2013) presented an overview of various methodologies for structural equation modelling (SEM), including partial least squares (PLS) and covariance-based SEM (CB-SEM). Covariance-based SEM (CB-SEM) employs the AMOS, EQS, LISREL, and MPlus software packages, while partial least squares (PLS) utilise the PLS-Graph, VisualPLS, SmartPLS, and WarpPLS software packages. The researcher utilised SmartPLS software to analyse the data and implemented

partial least squares (PLS) as the soft modelling approach to SEM in this investigation. The subsequent section elaborates on the justification for employing partial least squares.

3.9.4 Partial Least Square Approach to Structural Equation Modelling

The Partial Least Square Approach to Structural Equation Modelling (PLS-SEM) is employed to examine the causal connections among various latent factors of the study's participants. The utilisation of this approach is justified by the ability of the PLS-SEM to analyse and establish causal connections among multiple factors, as demonstrated in previous studies (Puteh & Azman Ong, 2017; Chin et al., 2020). The predictive power and measurement quality of the PLS-SEM is evaluated through the examination of multiple components to ascertain the reliability and validity of the model (Hair et al., 2021).

The initial step involves using the variance inflation factor (VIF), with a threshold value of less than 3.3 being deemed acceptable, for inclusion in the research assessing the presence of hidden lateral collinearity (Kock, 2015). The coefficient of determination (R^2) is a statistical measure that quantifies the ratio of variances in endogenous constructs that represent the model, thus indicating the explanatory power of the model. In academic studies focused on marketing matters, R^2 values of 0.26, 0.13 and 0.02 are categorised as substantial, moderate, or low, respectively (Cohen, 1988). To enhance the evaluation of the exogenous constructs' predictive influence, the inclusion of effect size (f^2) is required. Cohen (1998) offers criteria for evaluating the magnitude f^2 , where a value of 0.02 indicates modest influence, 0.15 indicates a medium effect, and 0.35 indicates a high effect. The predictive relevance, namely Q^2 , is used to evaluate the model's predictive power. It is determined through a blindfolding procedure, which involves assessing the model's performance in making predictions on fresh data that is excluded during the training phase of the model. This procedure is essential for evaluating the model's ability to make accurate predictions on

new, unseen data (Shmueli et al., 2019; Sarstedt et al., 2017). According to Shmueli et al. (2019), a value below zero indicates no predictive significance. Finally, to ascertain the connections among different constructs, the PLS bootstrapping procedure is employed to analyse the significance of path coefficients, comprising the critical value (t-value) and probability (p -value) (Hair et al., 2019; Sharma et al., 2017).

3.10 Analytical Framework

The analytical framework is constructed as below in Figure 3.3. It shows that farmers are more likely to adopt SFT if they are aware of it, believe it will improve their farm's performance, believe it is easy to use, and feel social pressure to adopt it. Additionally, farmers are more likely to adopt SFT if they have the resources and support they need to do so. The acceptance of SFT by farmers is expected to have a positive impact on food security. This is because SFT can help farmers to improve their yields, reduce waste, and use resources more efficiently. All of these factors can contribute to a more stable and sustainable food supply. The analytical process outlined in the framework involves using questionnaires and statistical analysis, specifically Smart-PLS, to test the relationships between the constructs in the model. This framework and further research would be needed to validate the model and determine the causal relationships between the constructs.

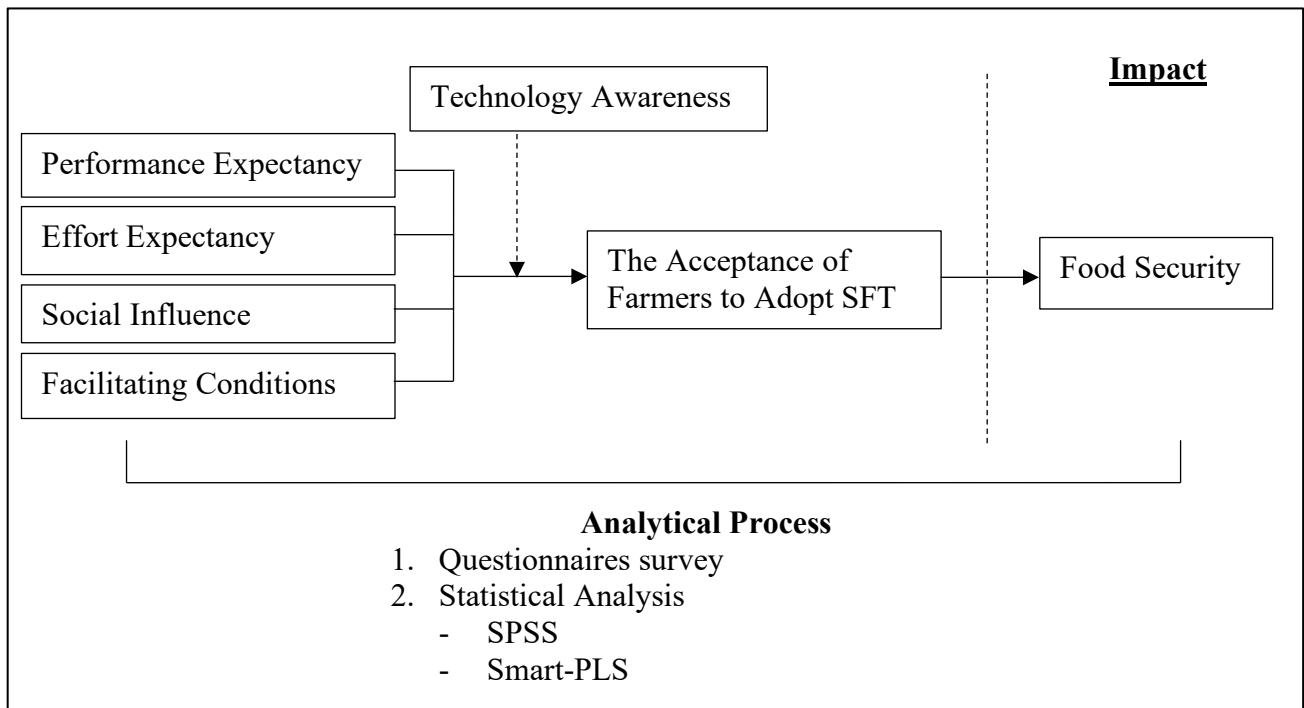


Figure 3. 3: Analytical Framework of The Acceptance of Farmers to Adopt SFT in Sustaining Food Security in Sarawak

3.11 Summary

The present study incorporated a discussion of the research methodologies in this chapter. Following a concise exposition of the research design and a discussion of the various types of research methodologies, the rationale for selecting the quantitative approach was subsequently justified. The research employed a survey questionnaire methodology to gather data, which was preceded by a pilot study consisting of forty participants to validate and ensure the instrument's consistency and validity. The research was conducted in the following locations: Kuching, Sarikei, Samarahan, Serian, and Kapit. In total, 330 questionnaires were gathered and evaluated at these sites. The instrument and design of the questionnaire, as well as the data analysis methods that were implemented (descriptive analysis and PLS-SEM), were elaborated upon. The approach to evaluating the measurement

model, the structural model, and the models' ability to provide a robust overview were then discussed. Following this, the analytical framework was examined.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Chapter Overview

This chapter pertains to the discussion of the empirical findings of the investigation. The empirical findings of the investigation are presented. SPSS is utilised to conduct the descriptive analysis, and Smart-PLS 4.0 is subsequently employed to evaluate the models, specifically the measurement model and structural model. A concise explanation and argument of the specific measures, threshold values, and the result are followed by additional analysis of the completed tests.

4.2 Data Preparation

Following the procedure for data compilation, which served as the preliminary stage of the data preparation procedure, the data was encoded into SPSS. SPSS was utilised to conduct the analysis of frequency in order to identify any instances of absent values in the dataset. As a result, the dataset included no incomplete values. The total number of questionnaires distributed personally and through representative area staff to the respondents was 300 sets, and only 280 were returned. Out of these 280 sets of answered questionnaires, in order to ascertain the validity and dependability of the data for this investigation, 33 questionnaire sets containing absent information, or unanswered queries were discarded. Hence only 247 sets of physical returned questionnaires were usable for analysis. Additionally, out of the 92 responses that were received from the questionnaires disseminated via WhatsApp and Google Forms, a mere 83 could be considered suitable for analysis. To ensure the validity and dependability of the data, 9 of returned questionnaires

were deemed unqualified to continue answering the preliminary questions were eliminated. As a result, there were 330 respondents in total eligible for this investigation.

After conducting an initial evaluation, 330 viable cases were imported into SPSS version 29 for additional analysis. Descriptive analysis results were produced by utilising the SPSS statistics database. An examination was conducted on missing data for each variable, and an analysis of the data was conducted to evaluate common method variance. Following this, the pre-existing data obtained from SPSS was exported to a Microsoft Excel file in order to furnish the Smart-PLS 4.0 software with pristine input. The assessment of the structural and measurement models was performed utilising the Smart-PLS 4.0 software.

4.2.1 Outliers

In general, statistical methods are susceptible to outliers. According to Tabachnick and Fidell (2007), an outlier is a situation where statistical data is erroneously influenced by an extreme value in one variable (univariate outlier) or an unusual combination of scores on two or more variables (multivariate outliers). SPSS's descriptive function computes both means and 5% trimmed means, providing valuable insights into potential challenges posed by outliers. The lack of substantial concern regarding the anomalies is indicated by the close similarity between the means of the two values (Pallant, 2007). The specific analysis results, presented in Table 2A of Appendices 2, demonstrate no statistically significant differences between the means and the 5% trimmed means (which involves excluding 5% of the highest and lowest values). As a result, no outliers are identified or removed from the dataset.

4.3 Respondents' Demographic Profile

The demographic profiles of the respondents were examined using descriptive statistics, which comprised measures such as the frequency and percentage. A total of 330

questionnaires were received, with males comprising 53.9% of the respondents and females comprising 46.1%. While 28.5% of the farmers who participated in this study were between the ages of 50 and 59, representing the second oldest age cohort. The marital status of 76.7% was the most prevalent, indicating that the respondents have familial obligations that may impact their agricultural choices and economic priorities. The ethnicity of Malay comprised 44.5% was the majority of the correspondents, followed by 37.3% of Dayak. The fact that 38.8% of the farmers completed secondary school might suggest that they had a rudimentary to moderate level of education, which might be adequate for conventional farming but could impede innovation. However, there were 13.6% of the respondents had no formal education based on face-to-face questionnaires survey. The farmers' farming expertise was additionally incorporated into the demographic data. The majority of respondents 72.7% had, as anticipated, between one and ten years of experience in farming. Lastly, 62.1% of the farmers reported a monthly income of less than RM1500, indicating that most respondents had low incomes, which might hinder their capacity to invest in their farms.

Table 4. 1: Respondent's Demographic (n=330)

Demographic variable	Frequency	Percentage (%)
Age		
Less than 20 year old	9	2.7
20 -29 years old	26	7.9
30-39 years old	74	22.4
40 – 49 years old	69	20.9
50-59 years old	94	28.5
60 years and above	58	17.6
Gender		
Male	178	53.9
Female	152	46.1
Marital status		
Single	68	20.6
Married	253	76.7
Others	9	2.7
Ethnicity		
Malay	147	44.5

Table 4.1 (continue)		
Dayak	123	37.3
Chinese	40	12.1
Others	20	6.1
Level of education		
No formal education	45	13.6
Primary school	57	17.3
Secondary school	128	38.8
Certificates	47	14.2
Diploma	23	7
University degree and above	30	9.1
Years of farming experience		
1 – 10 years	240	72.7
11- 20 years	41	12.4
21 – 30 years	18	5.5
31 – 40 years	9	2.7
41 years and above	22	6.7
Monthly income		
Below RM1500	205	62.1
RM1500 – RM3500	79	23.9
RM3500 – RM5500	26	7.9
RM5500 – RM8500	13	3.9
More than RM8500	7	2.1

4.4 Descriptive Statistics

The SPSS version 29 software was employed to calculate the mean, standard deviation, kurtosis, and skewness of each measure. Each variable was assessed using a seven-point Likert scale. One signifies "Strongly Disagree," and seven signifies "Strongly Agree."

Regarding performance expectancy, variable PE1 had the greatest mean score of 6.18, while variable PE2 followed with a mean score of 6.15. In contrast, variable PE5 exhibited the lowest mean score of 6.08. For effort expectancy, item EE4 received the highest mean score of 6.11. However, item EE2 and item EE5 received the second-highest mean score of 6.05. In contrast, EE1 and EE3 had the lowest mean score of 5.95. In addition, social influence for the item SI1 had the highest mean score of 6.01, followed by both

variables, SI2 and SI3, with an equal mean score of 5.99. Nevertheless, SI4 had the lowest mean score at 5.92. On the other hand, FC5 in the facilitating conditions variables had the highest mean score of 6.14 followed by variable FC1 with a mean score of 5.92. In contrast, variable FC2 had the lowest mean score of 5.80. Meanwhile, for a moderator variable which is technology awareness had the highest mean score of 6.11 for item AW5, followed by item AW2 with a similar mean score of 5.99. Nonetheless, the lowest mean score shared by both item AW3 and item AW4, at 5.88. For the acceptance of farmers to adopt SFT, variable AC1 received the highest mean score of 6.17, followed by variable AC4 with mean score of 6.14. Yet, variable AC3 had the lowest mean score of 6.09. Furthermore, food security received the highest mean score of 6.14 for item FS1, followed by FS5 with a mean score of 6.13. In addition, item FS3 held the lowest mean score at 6.01. Overall, all variables' mean scores ranged in between 5.80 to 6.18 indicates the respondent averagely rated agree to the statement given.

In addition, most items in the table are deemed acceptable, as the standard deviation is low demonstrates that all data are in proximity to the mean, indicating minimal dispersion in the data (Darling, 2022).

Furthermore, skewness and kurtosis values aim to ascertain the degree of flatness and peakiness exhibited by the data distribution. Additionally, it is employed to assess the normality of the data. The kurtosis and skewness tests unequivocally demonstrated that the gathered data is approximately normally distributed. This is supported by the fact that all obtained values of kurtosis (-10 +10) and skewness (-3 +3) fall within the acceptable range respectively. Exceeding these thresholds signifies a significant issue with the data's normality (Kline, 2016).

Table 4. 2: Descriptive Statistics for All Variables (n=330)

Construct	Indicator	Mean	SD	Kurtosis	Skewness
Performance expectancy	PE1	6.18	0.861	-0.882	-0.519
	PE2	6.15	0.820	-0.658	-0.475
	PE3	6.12	0.860	-1.356	-0.323
	PE4	6.11	0.840	-1.007	-0.394
	PE5	6.08	0.885	0.225	-0.617
Effort expectancy	EE1	5.95	0.969	-0.179	-0.567
	EE2	6.05	0.848	-0.740	-0.418
	EE3	5.95	0.955	-0.336	-0.486
	EE4	6.11	0.827	-0.471	-0.504
	EE5	6.05	0.908	-0.070	-0.623
Social influence	SI1	6.01	0.904	-0.260	-0.539
	SI2	5.99	0.823	-0.889	-0.246
	SI3	5.99	0.919	-0.535	-0.484
	SI4	5.92	0.843	-1.022	-0.125
	SI5	5.93	0.998	-0.033	-0.636
Facilitating Conditions	FC1	5.92	0.934	-0.303	-0.468
	FC2	5.80	0.931	-0.834	-0.198
	FC3	5.87	0.888	-0.891	-0.213
	FC4	5.82	0.912	-0.712	-0.254
	FC5	6.14	0.950	-0.324	-0.768
Technology Awareness	AW1	5.95	1.111	1.465	-1.180
	AW2	5.99	0.977	1.051	-0.940
	AW3	5.88	1.128	1.846	-1.199
	AW4	5.88	0.883	-1.027	-0.140
	AW5	6.11	0.872	-0.821	-0.463
The Acceptance of Farmers to Adopt SFT	AC1	6.17	0.812	-1.183	-0.395
	AC2	6.10	0.819	-1.283	-0.259
	AC3	6.09	0.818	-1.287	-0.242
	AC4	6.14	0.813	-0.729	-0.431
	AC5	6.10	0.883	0.295	-0.656
Food Security	FS1	6.14	0.823	-1.375	-0.291
	FS2	6.07	0.849	-0.505	-0.433
	FS3	6.01	0.879	-0.756	-0.321
	FS4	6.07	0.880	-0.523	-0.697
	FS5	6.13	0.847	-1.287	-0.348

4.5 Common Method Variance

The measurement error is illustrated by common method variance; additionally, this bias is exacerbated by the sociability of respondents who provide constructive feedback

(Chang & Eden, 2010). Concerns and observations pertaining to cross-sectional, single-source, self-reporting studies predominate among researchers. In general, the evaluation of the items comprising the questionnaire, or the indicators may be subject to bias. Undoubtedly, a prospective predisposition that respondents may exhibit while completing the survey or answering its questions constitutes a CMV. Therefore, the method of measurement, and not the structures described by the metrics, is the source of CMV. In order to mitigate the problem of common method bias, Podsakoff et al. (2003) suggested the implementation of several protocols, which can be categorised into the following five groups.

Firstly, the three distinct categories of separation exist: psychological, proximate, and temporal. Temporal separation causes a lapse in time between two measurements. In order to physically separate focal constructs in a survey, proximal separation employs additional activities or measures. Psychological separation is achieved through the implementation of cover stories or instructions that serve to diminish the correlation between predictor and criterion variables. In research, temporal separation attained through longitudinal studies is strongly advised because it reduces CMV. However, this method faces obstacles such as intricate designs, participant attrition, and determining the optimal time disparity. The presumption that bias diminishes and the true relationship remains constant over time necessitates meticulous deliberation (Podsakoff et al., 2012).

Secondly, one approach to mitigating bias in research is to obtain evaluations of predictors or criteria from multiple sources. In the context of management studies, for instance, researchers may collect employee self-evaluations followed by performance evaluations from administrators. The objective of these approaches is to mitigate biases that

individuals may have developed out of a desire to appear positive or consistent, as well as their present emotional states.

Thirdly, clarity issues and convoluted survey questions impede respondents' ability to comprehend and provide accurate responses (Podsakoff et al., 2003). This occurs when surveys employ ambiguously defined terms such as "occasionally" or "somewhat," or when terms possess multiple meanings. The respondents become uncertain about how to respond when queries are ambiguous and may resort to their typical response pattern (e.g., consistently selecting the extreme, the median, or agreeing with everything). By utilising uncomplicated and unambiguous queries devoid of double meanings is the optimal approach, as it facilitates individuals in providing accurate responses.

Fourthly, respondents' motivation to provide accurate responses can be increased by furnishing them with explicit instructions and details regarding the ways in which their responses will benefit the organisation or themselves (Hair et al., 2015; Podsakoff et al., 2003). In addition, encouraging responses can be facilitated by positive feedback or promising outcomes. In addition, participants are more likely to provide accurate responses when the survey is kept concise and repetitive queries are avoided.

Lastly, as a method of safeguarding the privacy of all respondents, fostering confidence and goodwill between researchers and study participants, rigorously upholding research ethics, and maintaining the integrity of research procedures, the principles of anonymity and confidentiality are maintained and applied. Moreover, in the course of research studies, the principles endorse autonomy and grant participants greater freedom and control.

In general, these procedures are executed throughout the study's design phase and the development of the questionnaire instrument. In this research, one of the aforementioned

protocols was implemented to protect the confidentiality of the participants. By ensuring respondent anonymity via the implementation of anonymous questionnaires, participants were able to readily and candidly supply responses that were not only precise but also impartial. The SPSS function known as Harman's Single Factor was employed to calculate the variance of the prevalent method. A substantial proportion of shared variance was assumed to be attributable to one factor or a common factor that explains the majority of the measure when exploratory factor analysis (EFA) identified it.

Moreover, according to the findings of Podsakoff et al. (2003), the proportion of variance accounted for by extraction sums of squared loadings should not surpass 50%. All 35 items included in this investigation were subjected to the SPSS test; the variance percentage was 33.834%, which is lower than the recommended threshold of 50%. Consequently, this study was deemed impartial in accordance with the principles of the conventional approach to research.

Table 4. 3: Harman's Single Factor

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.842	33.834	33.834	11.842	33.834	33.834
2	2.058	5.881	39.716			
3	1.567	4.478	44.194			
4	1.496	4.274	48.468			
5	1.431	4.088	52.555			
6	1.244	3.555	56.111			
7	1.126	3.218	59.328			
8	1.035	2.957	62.285			
9	1.001	2.861	65.146			
10	0.865	2.473	67.619			
11	0.792	2.263	69.882			
12	0.748	2.138	72.020			
13	0.711	2.031	74.051			
14	0.659	1.884	75.934			

Table 4.3 (continue)

15	0.637	1.819	77.753
16	0.621	1.775	79.529
17	0.593	1.695	81.224
18	0.579	1.654	82.878
19	0.549	1.568	84.446
20	0.510	1.457	85.904
21	0.479	1.368	87.272
22	0.457	1.306	88.578
23	0.433	1.238	89.816
24	0.407	1.161	90.977
25	0.364	1.040	92.018
26	0.354	1.012	93.030
27	0.333	0.950	93.980
28	0.324	0.927	94.907
29	0.317	0.905	95.812
30	0.292	0.835	96.647
31	0.269	0.768	97.415
32	0.256	0.731	98.147
33	0.242	0.691	98.837
34	0.226	0.645	99.482
35	0.181	0.518	100.00

4.6 Assessment of the Measurement Model

The initial step before evaluating the research model for hypothesis testing was to confirm the accuracy and consistency of the measurement model. The measurement model is composed of the associations between constructs and their corresponding indicator variables (Hair et al., 2014). Internal consistency, indicator reliability, and average variance extracted (AVE) were utilised to evaluate convergent validity. In addition, loadings, cross-loadings, and discriminant validity were assessed using the HTMT and the Fornell-Larcker, respectively. As a result, SRMR and NFI were employed to evaluate the goodness of fit.

4.6.1 Internal Consistency Reliability

In many cases, the initial criterion assessed is the dependability of internal consistency. The conventional measure for assessing internal consistency is Cronbach's alpha, which estimates reliability by examining the intercorrelations among the observed predictor variables. Cronbach's alpha aims to assess the reliability of internal consistency and is responsive to the number of elements included in the scale, often leading to potential underestimation of its effectiveness. Technically, utilising an alternative metric, specifically composite reliability (CR), is more suitable in light of this constraint (Hair et al., 2017). Based on rule of thumb for reliability criteria should be surpassed 0.70 threshold (Hair et al., 2019). The following reliability statistics demonstrate that the acceptance of farmers to adopt SFT was associated with the following CR values = 0.843, technology awareness = 0.855, effort expectancy = 0.896, facilitating conditions = 0.860, food security = 0.854, performance expectancy = 0.871, and social influence = 0.865. Consequently, the CR value, which signifies the extent to which the construct indicators reveal the latent, surpassed the conventional threshold of 0.70 in this investigation, fluctuating between 0.843 and 0.896 (Hair et al., 2006; Gefen et al., 2000). In essence, the items that assess the identical variable exhibit satisfactory convergence or internal consistency levels.

Table 4. 4: Internal Consistency Reliability

Construct	No. of item	Cronbach alpha	Composite reliability (CR)
The acceptance of farmers to adopt SFT	5	0.767	0.843
Technology awareness	5	0.793	0.855
Effort expectancy	5	0.855	0.896
Facilitating conditions	5	0.797	0.860
Food security	5	0.788	0.854
Performance expectancy	5	0.815	0.871
Social influence	5	0.805	0.865

4.6.2 Indicator Reliability

Commonly, the magnitude of the peripheral loading is referred to as indicator reliability. More significant outer loadings on a construct indicate that the construct captures a great deal of similarity between the associated indicators. It is essential that the outer loadings of all indicators attain a minimum of statistical significance. In the same way that high loadings on factors indicate that items within a construct are highly converged, Hair et al. (2010) asserted that estimates of standardised loadings should be at least 0.5 significant. The reliability statistics on Table 4.5 demonstrated the loading values span a range of 0.625 to 0.840.

Table 4. 5: Indicator Reliability

Construct	Items	Outer loading
The acceptance of farmers to adopt SFT	AC1	0.678
	AC2	0.683
	AC3	0.695
	AC4	0.776
	AC5	0.761
Technology awareness	AW1	0.712
	AW2	0.786
	AW3	0.691
	AW4	0.759
	AW5	0.730
Effort expectancy	EE1	0.813
	EE2	0.780
	EE3	0.795
	EE4	0.790
	EE5	0.795
Facilitating conditions	FC1	0.752
	FC2	0.788
	FC3	0.718
	FC4	0.688
	FC5	0.765
Food security	FS1	0.763
	FS2	0.750
	FS3	0.732
	FS4	0.766
	FS5	0.654

Table 4.5 (continue)		
Performance expectancy	PE1	0.749
	PE2	0.811
	PE3	0.812
	PE4	0.786
	PE5	0.625
Social influence	SI1	0.840
	SI2	0.811
	SI3	0.691
	SI4	0.719
	SI5	0.683

4.6.3 Convergent Validity

Convergent validity refers to the degree to which a given measure exhibits favourable comparisons with alternative steps of the same construct. The evaluation of convergent validity involves the analysis of the average variance extracted (AVE). Therefore, convergent validity pertains to the extent to which specific indicators accurately represent a converging construct, as opposed to measures that examine different constructs (Urbach & Ahlemann, 2010). The greatest mean value of the squared loadings of the construct-related indicators constitutes this criterion. Alternatively stated, it refers to the extent to which the variability of its indicators is accounted for by a latent construct (Hair et al., 2016). The AVE value for the acceptance of farmers to adopt SFT was 0.518, technology awareness was 0.542, effort expectancy was 0.632, facilitating conditions were 0.552, food security was 0.539, performance expectancy was 0.577 and social influence was 0.564. The observed values, ranging from 0.518 to 0.632, all surpassed the AVE threshold of 0.50 (Hair et al., 2013; Barclays et al., 1995). Thus, on average, each variable in this analysis would elucidate the variance of the indicators. Based on their parameter estimates and statistical significance, the outcome showed that each of the seven constructs, namely the acceptance of farmers to adopt SFT, technology awareness, effort expectancy, facilitating conditions, food security,

performance expectancy, and social influence, are all valid measures of its respective construct. Convergent validity was therefore attained in this investigation.

Table 4. 6: Convergent Validity

Construct	No. of Item	Average Variance Extracted (AVE)	Convergent Validity
The acceptance of farmers to adopt SFT	5	0.518	Yes
Technology awareness	5	0.542	Yes
Effort expectancy	5	0.632	Yes
Facilitating conditions	5	0.552	Yes
Food security	5	0.539	Yes
Performance expectancy	5	0.577	Yes
Social influence	5	0.564	Yes

4.6.4 Discriminant Validity

Discriminant validity refers to the extent to which a particular construct can be distinguished based on empirical criteria (Hair et al., 2016). In order to evaluate the discriminant validity of the measurement model, the subsequent criteria may be applied: 1) The cross-loading, 2) The heterotrait-monotrait ratio (HTMT), and 3) The Fornell and Larcker.

The item loadings and cross-loadings that establish a relationship between each item and both its intended construct (e.g., loadings) and the other constructs (e.g., cross-loadings) are presented in Table 4.7. According to Ramayah et al. (2018), in this particular context, the magnitude of the loadings of the indicators on the designated latent variable must be greater than the magnitude of the loadings on all other latent variables in the model. Refer to the data presented in Table 4.7, the loading values for various factors influencing the acceptance of farmers to adopt SFT were as follows: technology awareness (0.691-0.786), social influence (0.683-0.840), effort expectancy (0.780-0.813), facilitating conditions (0.688-0.788), food security (0.654-0.766), and performance expectancy (0.625-0.812). The

researcher employed a significance level of 0.5 for loadings, as recommended by Hair et al. (2010). The cross-loadings for each item measuring a particular construct was found to be greater than the cross-loadings for that construct with all other constructs, as indicated in Table 4.7. As a result, this study could conclude that the model construct had a strong construct validity. As shown in Table 4.7, each bolded value was greater than 0.5, satisfying the necessary criterion.

Table 4. 7: Loadings and Cross Loadings

	AC	AW	EE	FC	FS	PE	SI
AC1	0.678	0.368	0.305	0.321	0.357	0.332	0.317
AC2	0.683	0.353	0.380	0.262	0.345	0.372	0.359
AC3	0.695	0.330	0.250	0.292	0.400	0.328	0.343
AC4	0.776	0.354	0.365	0.407	0.489	0.474	0.439
AC5	0.761	0.377	0.349	0.366	0.441	0.399	0.347
AW1	0.300	0.712	0.498	0.420	0.364	0.339	0.360
AW2	0.343	0.786	0.477	0.485	0.336	0.399	0.378
AW3	0.270	0.691	0.532	0.401	0.316	0.352	0.344
AW4	0.375	0.759	0.451	0.468	0.352	0.372	0.376
AW5	0.467	0.730	0.379	0.421	0.312	0.389	0.456
EE1	0.372	0.453	0.813	0.485	0.410	0.511	0.457
EE2	0.383	0.526	0.780	0.484	0.458	0.492	0.446
EE3	0.304	0.508	0.795	0.410	0.351	0.456	0.418
EE4	0.398	0.499	0.790	0.469	0.354	0.516	0.483
EE5	0.353	0.477	0.795	0.464	0.359	0.452	0.473
FC1	0.324	0.434	0.480	0.752	0.333	0.417	0.443
FC2	0.374	0.501	0.445	0.788	0.379	0.441	0.477
FC3	0.335	0.42	0.448	0.718	0.386	0.388	0.423
FC4	0.322	0.358	0.347	0.688	0.375	0.324	0.342
FC5	0.362	0.491	0.449	0.765	0.452	0.424	0.524
FS1	0.420	0.317	0.312	0.363	0.763	0.414	0.421
FS2	0.364	0.281	0.386	0.404	0.750	0.433	0.407
FS3	0.487	0.377	0.366	0.428	0.732	0.413	0.395
FS4	0.469	0.393	0.382	0.392	0.766	0.372	0.360
FS5	0.308	0.266	0.354	0.302	0.654	0.340	0.350
PE1	0.370	0.429	0.467	0.477	0.407	0.749	0.444
PE2	0.436	0.393	0.484	0.440	0.434	0.811	0.455

Table 4.7 (continue)							
PE3	0.423	0.338	0.480	0.373	0.367	0.812	0.355
PE4	0.468	0.360	0.459	0.395	0.449	0.786	0.393
PE5	0.311	0.434	0.450	0.375	0.384	0.625	0.368
SI1	0.407	0.424	0.471	0.481	0.378	0.453	0.840
SI2	0.401	0.422	0.480	0.502	0.471	0.428	0.811
SI3	0.300	0.297	0.351	0.442	0.350	0.358	0.691
SI4	0.394	0.455	0.475	0.471	0.363	0.370	0.719
SI5	0.378	0.364	0.363	0.345	0.406	0.366	0.683

The Fornell and Larcker criterion represents the second approach to evaluating discriminant validity. The outcomes of this evaluation are generated by employing the algorithm function of Smart-PLS. The AVE of a latent variable must exceed the squared correlation between that variable and all other variables in order to satisfy this criterion for this test (Ramayah et al., 2018). Calculating the square root of the AVE along the diagonal is an alternative method for evaluating this; the result should surpass the correlation along the opposite diagonal (Ramayah et al., 2018). As shown in Table 4.8, every element along the principal diagonal is elevated relative to the off-diagonal elements in its particular row and column. To provide an example, the square root of the average variance extracted (AVE) for effort expectancy in the third row and column was 0.795, which exceeded the corresponding values of 0.459 and 0.620 for off-diagonal elements in the second row, and 0.585, 0.488, and 0.613 for the aforementioned column of off-diagonal elements.

Moreover, the square roots of AVE for the following constructs were calculated: the acceptance of farmers to adopt SFT (0.720), technology awareness (0.736), effort expectancy (0.795), facilitating conditions (0.743), food security (0.734) performance expectancy (0.760), and social influence (0.751). These values are all greater than the corresponding constructs in the rows and columns. A critical evaluation of the performance

of cross-loadings and the criterion proposed by Fornell and Larcker to assess discriminant validity revealed that both methods failed to identify issues related to discriminant validity consistently (Henseler et al., 2015). Therefore, Henseler et al. (2015) suggested evaluating the correlations using the Heterotrait-Monotrait Ratio (HTMT) as a potential solution.

Table 4. 8: Fornell and Larcker

	AC	AW	EE	FC	FS	PE	SI
AC	0.720						
AW	0.493	0.736					
EE	0.459	0.620	0.795				
FC	0.463	0.596	0.585	0.743			
FS	0.570	0.454	0.488	0.519	0.734		
PE	0.535	0.506	0.613	0.538	0.537	0.760	
SI	0.505	0.529	0.575	0.597	0.526	0.528	0.751

In evaluating discriminant validity, the Heterotrait-Monotrait Ratio (HTMT) is the third and most dependable method (Henseler, 2015). The indicators' ratio of correlations within a construct against to ratio of correlations within different constructs is denoted as HTMT (Ramayah et al., 2018). According to the criteria, the HTMT value must not surpass 0.9; failure may compromise the discriminant validity (Ramayah et al., 2018). Henseler et al. (2015) argued that a more conservative threshold value of 0.85 appears warranted when the path model structures are conceptually distinct. The elements in bold represent the HTMT values produced by the Smart-PLS algorithm. The obtained values indicate that the discriminant validity ascertained in this study is satisfied when each value is below 0.9. However, because PLS-SEM operates without distributional assumptions, conventional parametric significance tests cannot be utilised to determine whether the HTMT statistic significantly deviates from 1. The results are displayed in Table 4.9. In its entirety, all requisite validity and reliability assessments were performed on the measurement model,

thereby satisfying every recommended criterion. The results of the measurement model level tests; all values did not exceed 0.9, validated the suitability and acceptability of the indicators utilised in this research for the structural model analyses.

Table 4. 9: Heterotrait-Monotrait Ratio (HTMT)

	AC	AW	EE	FC	FS	PE	SI
AC							
AW	0.611						
EE	0.561	0.768					
FC	0.585	0.744	0.705				
FS	0.710	0.564	0.593	0.647			
PE	0.664	0.637	0.736	0.673	0.671		
SI	0.635	0.642	0.686	0.744	0.660	0.655	

4.7 Goodness of Fit Indices

The model fitness criteria assist in determining the magnitude of the discrepancy between the implied model and the empirical correlation matrix. The standardised root mean square residual (SRMR) is a metric generated by Smart-PLS. A model is considered a reasonable fit if the SRMR is below 0.08 (Hu & Bentler, 1998). Some employ a more relaxed threshold of less than 0.10 (Henseler et al., 2014). In contrast, NFI's value remains within an acceptable range, specifically surpassing 0.5 and approaching 1, a threshold at which a fit is deemed satisfactory (Zainab et al., 2019). The study model achieved a satisfactory level of model fit, as evidenced by the SRMR value of 0.085 (<0.10) for the model and the NFI value of 0.710 (between 0.5 to 1.0) for the model. These values indicated that the model enhances the fit by 71.10% compared to the null or independent model. The fit and fitness indices for the study model are satisfactory, as presented in Table 4.10.

Table 4. 10: Goodness of Fit Indices

Index	Saturated	Estimated
SRMR	0.064	0.085
NFI	0.719	0.710

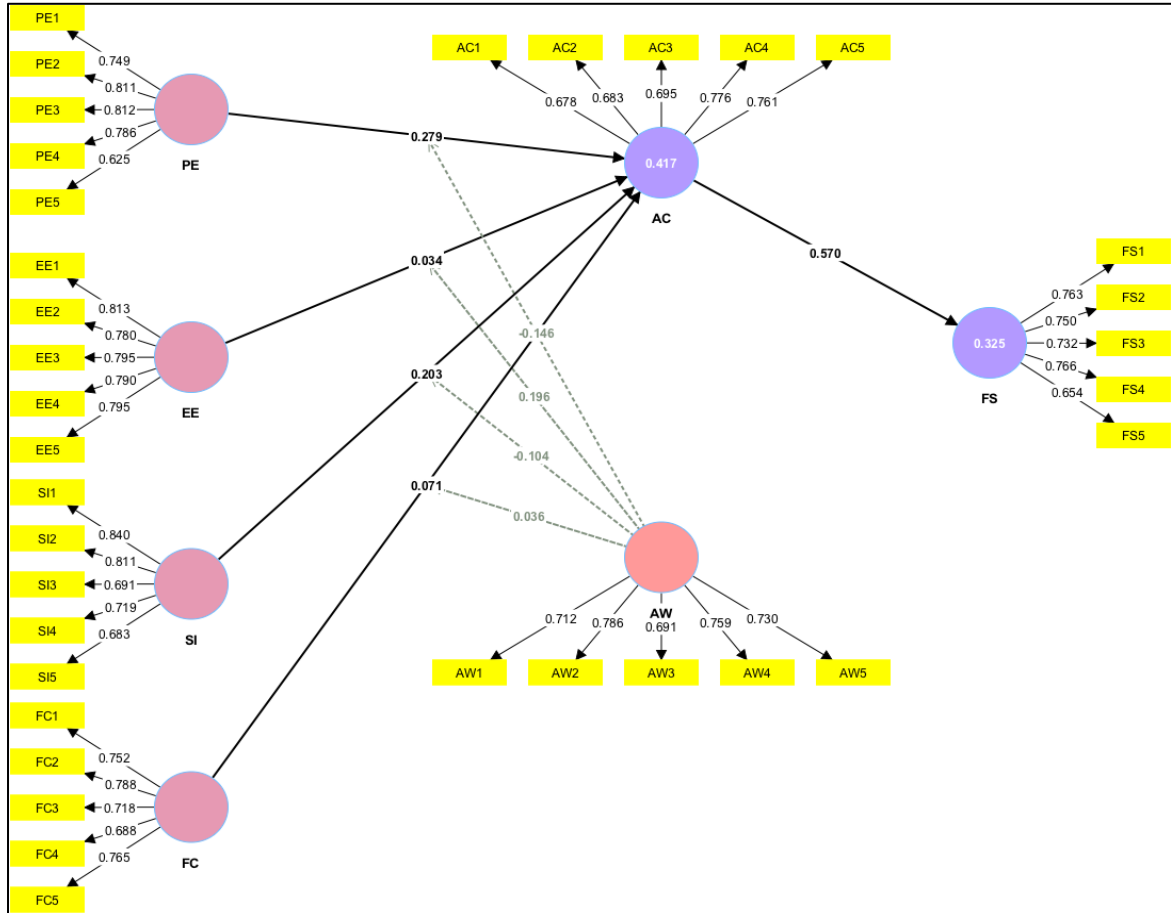


Figure 4. 1: Assessment of the Measurement Model

Figure 4.1 demonstrates the loadings for each of the items and beta values for the studied variables. In conclusion, the measurement model in this study exhibited satisfactory reliability and construct validity, which was evidenced by adequate reliability, convergent validity, and discriminant validity.

4.8 Assessment of the Structural Model

After verifying the reliability and validity of the construct utilised in this investigation, the researcher proceeded to evaluate the outcomes of the structural model. The hypothesised relationships between exogenous and endogenous variables were incorporated into the structural model. Alternatively stated, an examination was conducted on the internal model of this research. The researcher initially conducted a collinearity assessment of the structural model. Subsequently, while blindfolded, they evaluated the structural model's predictive relevance (Q^2), significance and relevance (R^2), and effect sizes (f^2).

4.8.1 Collinearity Test

In assessing common method bias, the collinearity test is an additional statistical examiner. An examination of both vertical and lateral collinearity is conducted concurrently using this systematic approach (Kock & Lynn, 2012). This examination was conducted using Smart-PLS. Collinearity, or inter-correlation, is a statistical condition characterised by a strong correlation among the independent variables. This limitation is unique to multiple regression models; basic regressions do not possess it.

According to Montgomery (2001), a rule of thumb dictates that the associated regression coefficients are inadequately estimated due to multicollinearity if either of the VIF values surpasses 5 or 10. A VIF value below 3.3 was suggested as the optimal threshold for this test; any higher than that value would suggest the presence of pathological collinearity, which could indicate common method bias contaminating the model (Kock, 2015). Consequently, the study did not indicate collinearity, as all VIF values were below 3.3; results were illustrated on Table 4.11.

Table 4. 11: Collinearity Test

Constructs	Items	Outer VIF	Inner VIF
The acceptance of farmers to adopt SFT	AC1	1.459	1.000
	AC2	1.402	
	AC3	1.459	
	AC4	1.614	
	AC5	1.580	
Technology awareness	AW1	1.981	1.942
	AW2	2.197	
	AW3	1.463	
	AW4	1.537	
	AW5	1.357	
Effort expectancy	EE1	2.089	2.272
	EE2	1.810	
	EE3	1.982	
	EE4	1.715	
	EE5	2.048	
Facilitating conditions	FC1	1.635	2.139
	FC3	1.430	
	FC4	1.368	
	FC5	1.568	
	FC1	1.635	
Food security	FS1	1.591	
	FS2	1.647	
	FS3	1.366	
	FS4	1.540	
	FS5	1.449	
Performance expectancy	PE1	1.758	1.829
	PE2	1.934	
	PE3	2.036	
	PE4	1.829	
	PE5	1.829	
Social influence	SI1	2.064	1.927
	SI2	1.964	
	SI3	1.546	
	SI4	1.417	
	SI5	1.354	

4.8.2 Bootstrapping and Path Coefficient

As Chow (2011) described, bootstrapping is a resampling method that estimates models for each of the numerous sub-samples generated from an empirical distribution of the observed data. The non-parametric bootstrap procedure is utilised in PLS to assess the

significance of coefficients, including outer weights, outer loadings, and path coefficients (Efron & Tibshirani, 1986; Davison & Hinkley, 1997). Consequently, to examine the proposed hypotheses and the path coefficient (β), the researcher employed the bootstrapping method with a sub-sample size of 10,000 and a one-tailed t-test (Hair et al., 2019). Each sub-sample contained 330 cases.

Additionally, it is necessary to analyse the path coefficients, which symbolise the postulated connections among the constructs (Ramayah et al., 2018). Conversely, PLS functions as a non-parametric analysis, devoid of any assumptions concerning the distribution of the data. As a consequence, a Type I error may occur if the t-value is inflated or deflated in the absence of normally distributed data (Ramayah et al., 2018). According to Hair et al. (2017), the optimal range for the path coefficient values is between +1 and -1. Coefficients that approach +1 signify the existence of a strong positive correlation, whereas those that approach -1 signify a strong negative correlation. As stated by Hair et al. (2016), the bootstrapping standard error of a coefficient is ultimately utilised to ascertain its significance. The t-statistics provided insights into the significance of each relationship. As a result, the t-value, p-value, path coefficient, and standard error are provided as outcomes. Furthermore, the results function as a standard against which the proposed hypothesis of the study can be either confirmed or refuted.

4.8.3 Hypotheses Testing

The examination of the path coefficient between the confidence interval and latent variables is conducted to evaluate the credibility of the proposed hypotheses in the research. In terms of the path coefficient, a one-tailed test establishes three specific rules for the path coefficient: a t-value > 2.33 when the p-value < 0.01 , a p-value < 0.05 when the t-value > 1.645 , and a t-value < 0.10 when the t-value > 1.28 (Hair et al., 2017). Regarding the

confidence interval bias, this supports the significance and applicability of the structural model. The results were generated using the Smart-PLS bootstrapping test.

4.8.4 Findings of the Hypotheses Testing

The outcomes of the hypotheses testing are summarised on Table 4.12.

H1: Performance expectancy has a positive relationship towards the acceptance of farmers to adopt SFT.

Hypotheses 1 examined the relationship between PE and the acceptance of farmers to adopt SFT. The outcomes for this hypothesis showed that PE positively affects the acceptance of farmers to adopt SFT ($\beta = 0.279$, $t = 4.662$, $p = 0.000 < 0.05$), with the observed 95% confidence interval bias (0.176;0.373). To clarify, the study rejects the null hypothesis on the grounds that the t-value exceeds the critical value, and the p-value is below the predetermined significance level of 5%. As a result, it is determined that the relationship between performance expectancy and the acceptance of farmers to adopt SFT is supported.

H2: Effort expectancy has a positive relationship towards the acceptance of farmers to adopt SFT.

Hypotheses 2 examined the relationship between EE and the acceptance of farmers to adopt SFT. The outcomes for this hypothesis showed that EE negatively affects the acceptance of farmers to adopt SFT ($\beta = 0.034$, $t = 0.485$, $p = 0.314 > 0.05$), with the observed 95% confidence interval bias (-0.081;0.150). To clarify, the study does not reject the null hypothesis on the grounds that the p-value exceeds the 5% significance level, and the t-value is less than the critical value. As a result, it is determined that the relationship between effort expectancy and the acceptance of farmers to adopt SFT is not supported.

H3: Social influence has a positive relationship towards the acceptance of farmers to adopt SFT.

Hypotheses 3 examined the relationship between SI and the acceptance of farmers to adopt SFT. The outcomes for this hypothesis showed that SI positively affects the acceptance of farmers to adopt SFT ($\beta = 0.203$, $t = 3.225$, $p = 0.001 < 0.05$), with the observed 95% confidence interval bias (0.096;0.304). To clarify, the study rejects the null hypothesis on the grounds that the t-value exceeds the critical value, and the p-value is below the predetermined significance level of 5%. As a result, it is determined that the relationship between social influence and the acceptance of farmers to adopt SFT is supported.

H4: Facilitating conditions has a positive relationship towards the acceptance of farmers to adopt SFT.

Hypotheses 4 examined the relationship between effort expectancy and the acceptance of farmers to adopt SFT. The outcomes for this hypothesis showed that FC negatively affects the acceptance of farmers to adopt SFT ($\beta = 0.071$, $t = 0.934$, $p = 0.175 > 0.05$), with the observed 95% confidence interval bias (-0.056;0.197). To clarify, the study does not reject the null hypothesis on the grounds due to the fact that both the t-value and p-value exceed the critical value and the 5% significance level, respectively. As a result, it is determined that the relationship between effort expectancy and the acceptance of farmers to adopt SFT is not supported.

H6: The acceptance of farmers to adopt SFT has a positive relationship towards sustaining food security in Sarawak.

Hypotheses 6 examined the relationship between the acceptance of farmers to adopt SFT and food security. The outcomes for this hypothesis showed that the acceptance of

farmers to adopt SFT positively affects food security ($\beta = 0.570$, $t = 14.349$, $p = 0.000 < 0.05$), with the observed 95% confidence interval bias (0.496;0.628). To clarify, the study rejects the null hypothesis on the grounds that the t-value exceeds the critical value, and the p-value is below the predetermined significance level of 5%. As a result, it is determined that the relationship between the acceptance of farmers to adopt SFT and food security is supported.

4.9 Moderation Analysis

The term moderating variable denotes a factor that impacts the direction and magnitude of an antecedent that affects an outcome (Aguinis et al., 2017). Moderation is defined statistically as the degree to which the value of a moderator variable influences the relationship between an independent and dependent variable (Dawson, 2014). Furthermore, moderating variables are crucial in determining whether the relationship between two variables is consistent across groups. Generally, a moderating model examines the circumstances or individuals for whom a particular variable significantly accounts for or influences a dependent variable (Frazier et al., 2004).

There were four hypotheses involving one moderator for the same relationship. First, it was hypothesized that technology awareness moderates a positive relationship between performance expectancy and the acceptance of farmers to adopt SFT such that technology awareness would buffer be higher, the relationship between performance expectancy and the acceptance of farmers weakens. Second, to test the technology awareness moderates a positive relationship between effort expectancy and the acceptance of farmers to adopt SFT such the higher level of technology awareness would weaken the positive relationship

between effort expectancy and the acceptance of farmers to adopt SFT. Third, technology awareness moderates a positive relationship between social influence and the acceptance of farmers to adopt SFT such that technology awareness increases, the relationship between social influence and the acceptance of farmers weakens. Finally, to test the technology awareness moderates a positive relationship between facilitating conditions and the acceptance of farmers to adopt SFT such the higher level of technology awareness would weaken the positive relationship between facilitating conditions and the acceptance of farmers to adopt SFT. The moderator effect is discussed next.

H5a: Technology awareness moderates a positive relationship between performance expectancy and the acceptance of farmers to adopt SFT.

H5a examined the technology awareness relationship between PE and the acceptance of farmers to adopt SFT. The outcomes for this hypothesis showed that technology awareness is moderate in the relationship between PE and the acceptance of farmers to adopt SFT ($\beta = -0.146$, $t = 2.451$, $p = 0.007 < 0.05$), with the observed 95% confidence interval bias (-0.240; -0.046). To clarify, the study rejects the null hypotheses on the grounds that the t-value exceeds the critical value, and the p-value is below the predetermined significance level of 5%. The two lines in Figure 4.4 exemplify the technology awareness relationship between the acceptance of farmers to adopt SFT and performance expectancy for low and high levels of moderator construct technology awareness. A low level of AW is one standard deviation unit below its average, while a high level of AW is one standard deviation unit above its average. The slope of the high moderator is a bit flatter due to the negative moderating effect by the $\beta = -0.146$ in the relationship between interaction term endogenous construct. Hence, this indicates the relationship between AC and PE becomes weaker with

high levels of the moderator construct AW. However, for a low AW line slope is steeper indicating the relationship between PE and AC becomes stronger. Although the effect is not great, it is still significant ($p=0.007<0.05$). The result of the analysis is shown in Table 4.13 and Figure 4.4.

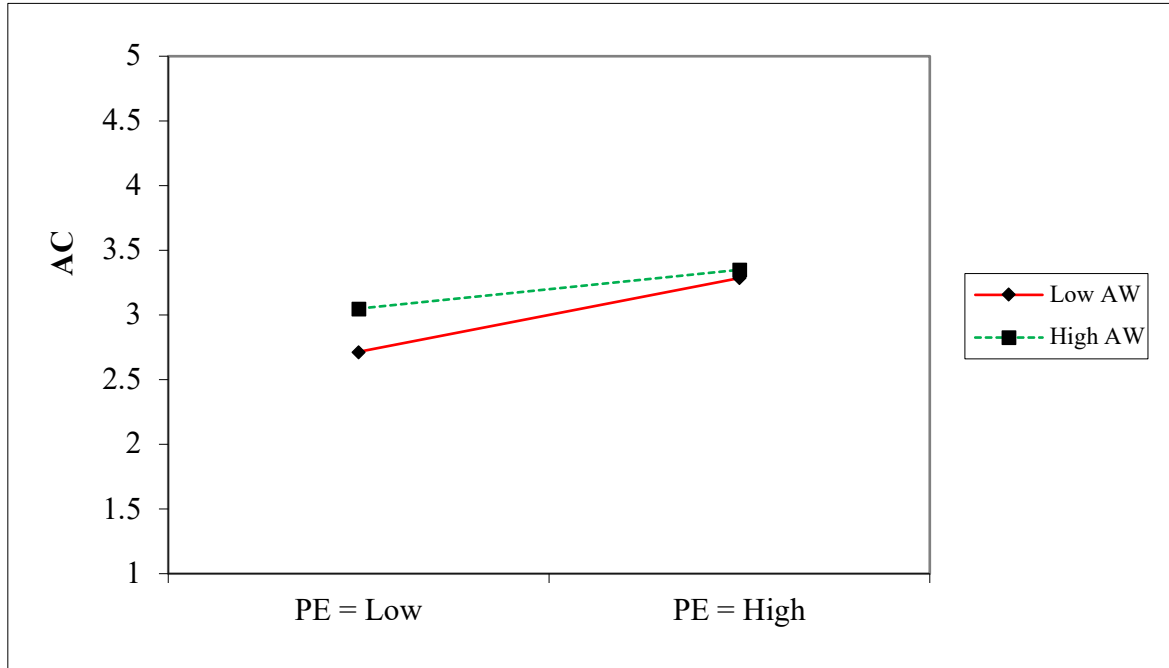


Figure 4. 2: Plotting the Interaction of Technology Awareness in PE-AC Relationship

H5b: Technology awareness moderates a positive relationship between effort expectancy and the acceptance of farmers to adopt SFT.

H5b examined the technology awareness relationship between EE and the acceptance of farmers to adopt SFT. The outcomes for this hypothesis showed that technology awareness is moderate in the relationship between EE and the acceptance of farmers to adopt SFT ($\beta = 0.196$, $t = 2.374$, $p = 0.009 < 0.05$), and the observed 95% confidence interval bias (0.065;0.331). To clarify, the study rejects the null hypothesis on the grounds that the t-value exceeds the critical value, and the p-value is below the predetermined significance level of

5%. The two lines in Figure 4.5 exemplify the technology awareness relationship between the acceptance of farmers to adopt SFT and performance expectancy for low and high levels of moderator construct technology awareness. A low level of AW is one standard deviation unit below its average, while a high level of AW is one standard deviation unit above its average. Furthermore, the slope of the high AW line is steeper because of the positive moderating, as expressed in the value of $\beta = 0.196$ relationship between the interaction term endogenous construct. Hence, the relationship between AC and EE becomes stronger with high levels of the moderator construct AW. This indicates that the relationship between EE and AC is stronger for high AW. However, for a low AW line slope is much flatter indicating the relationship between EE and AC becomes weaker. The result of the analysis is shown in Table 4.13 and Figure 4.5.

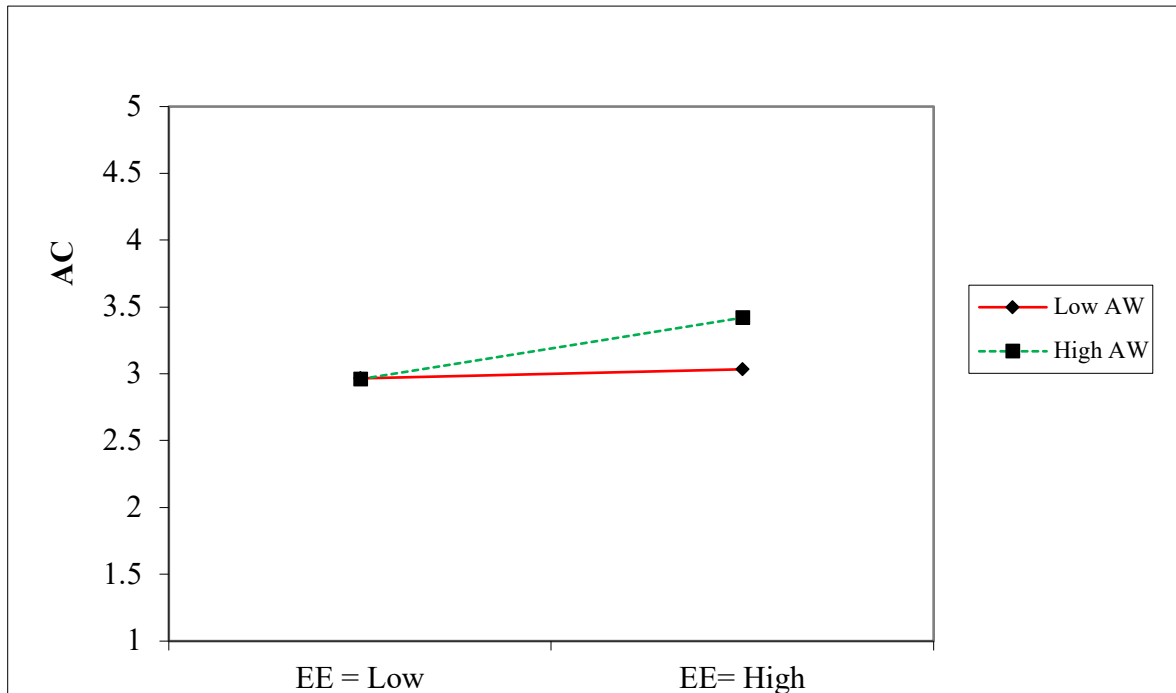


Figure 4. 3: Plotting the Interaction of Technology Awareness in EE-AC Relationship

H5c: Technology awareness moderates a positive relationship between social influence and the acceptance of farmers to adopt SFT.

H5c examined the technology awareness relationship between SI and the acceptance of farmers to adopt SFT. The outcomes for this hypothesis showed that technology awareness does not moderate in the relationship between SI and the acceptance of farmers to adopt SFT ($\beta = -0.104$, $t = 1.507$, $p = 0.066 > 0.05$), and the observed 95% confidence interval bias (-0.211, 0.01). To clarify, the study does not reject the null hypothesis on the grounds that the p-value exceeds the 5% significance level, and the t-value is less than the critical value, which means that the technology awareness relationship between social influence and the acceptance of farmers to adopt SFT is not significantly. The results of this moderator are displayed in Table 4.13. This effect is not plotted because no moderating effect is found.

H5d: Technology awareness moderates a positive relationship between facilitating condition and the acceptance of farmers to adopt SFT.

H5d examined the technology awareness relationship between FC and the acceptance of farmers to adopt SFT. The outcomes for this hypothesis showed that technology awareness does not moderate the relationship in between FC and the acceptance of farmers to adopt SFT ($\beta = 0.036$, $t = 0.403$, $p = 0.343 > 0.05$), and the observed 95% confidence interval (-0.113;0.183 To clarify, the study does not reject the null hypothesis on the grounds that the p-value exceeds the 5% significance level, and the t-value is less than the critical value, which means that the technology awareness relationship between FC and the acceptance of farmers to adopt SFT is not significantly. The results of this moderator are displayed in Table 4.13. This effect is not plotted because no moderating effect is found.

Table 4. 12: Result of Hypotheses Testing

Hypotheses	Relationship	Path Coefficient (β)	SD	T statistics	P values	Confidence Interval Bias	Decision	Conclusion
H1	PE -> AC (+)	0.279	0.060	4.662	0.000**	0.176;0.373	Reject Ho	Supported
H2	EE -> AC (-)	0.034	0.070	0.485	0.314	- 0.081;0.150	Do not reject Ho	Not supported
H3	SI -> AC (+)	0.203	0.063	3.225	0.001**	0.096;0.304	Reject Ho	Supported
H4	FC -> AC (-)	0.071	0.076	0.934	0.175	- 0.056;0.197	Do not reject Ho	Not supported
H6	AC -> FS (+)	0.570	0.040	14.349	0.000**	0.496;0.628	Reject Ho	Supported

* $P < 0.01$, ** $P < 0.05$, *** $P < 0.10$

Table 4. 13: Result of the Moderation Effect

Hypotheses	Relationship	Path Coefficient (β)	SD	T statistics	P values	Confidence Interval Bias	Decision	Conclusion
H5a	AW x PE -> AC (+)	-0.146	0.060	2.451	0.007**	-0.240;-0.046	Reject Ho	Moderation
H5b	AW x EE -> AC (+)	0.196	0.083	2.374	0.009**	0.065;0.331	Reject Ho	Moderation
H5c	AW x SI -> AC (-)	-0.104	0.069	1.507	0.066	-0.211, 0.01	Do not reject Ho	No moderation
H5d	AW x FC -> AC (-)	0.036	0.090	0.403	0.343	-0.113;0.183	Do not reject Ho	No moderation

*P<0.01, **P<0.05, ***P<0.10

4.10 Coefficient of Determination (R Square)

The coefficient of determination quantifies the extent to which the model can accurately anticipate the values of a particular endogenous construct. It is calculated as the square of the correlation between the observed and predicted values. A higher value of R square (R^2) suggests a greater prediction accuracy. Determining suitable R^2 values may be difficult since it relies on the model's intricacy and the research's rigour. In academic studies focused on marketing matters, R^2 values of 0.26, 0.13, and 0.02 are categorised as substantial, moderate, or low, respectively (Cohen, 1998). The coefficient of determination (R^2) in this study is 0.417 and 0.325, indicating a significant level of predictive accuracy.

Table 4. 14: Result of Coefficient Determination (R^2)

Construct	R Square	Level of Acceptance
The acceptance of farmers to adopt SFT	0.417	Substantial
Food Security	0.325	Substantial

4.11 Effect Size (f Square)

Furthermore, by assessing the R^2 values of all endogenous constructs, one may identify the impact of excluding a specific exogenous construct from the model. The change in the R^2 value can then be used to ascertain the significance of the removed construct on the endogenous constructs. This metric is commonly known as the f square (f^2) impact size. Cohen (1988) offers criteria for evaluating the magnitude of f^2 , where a value of 0.02 indicates a modest influence, 0.15 indicates a medium effect, and 0.35 indicates a high effect. A diminutive effect size, shown by a value below 0.02, signifies the absence of an effect. The results obtained from Smart-PLS indicated that the impact of performance expectancy (0.073), technology awareness (0.032) and social influence (0.037) on the f^2 value for the acceptance of farmers to adopt SFT is relatively small. However, it is worth noting that EE and FC do not have a significant effect. Furthermore, the significant impact of the acceptance

of farmers to adopt SFT (0.481) played a crucial role in generating the f^2 for food security. Table 4.15 displays the outcome of the effect size (f^2).

Table 4. 15: Result of Effect Size (f^2)

Construct	The Acceptance of Food Security Farmers to Adopt SFT	Effect Size
The acceptance of farmers to adopt SFT	0.481	Substantial
Technology awareness	0.032	Small
Effort expectancy	0.001	No effect
Facilitating conditions	0.004	No effect
Performance expectancy	0.073	Small
Social influence	0.037	Small

4.12 Predictive Relevance (Q Square)

The blindfolding procedure implemented in Smart-PLS yields the Q square (Q^2), which is utilised to assess out-of-sample predictive power or predictive relevance. Blindfolding is classified as a form of sample reuse because it involves excluding the data point from the indicators of the endogenous construct and estimating the parameters using the remaining data points. (Chin, 1998; Henseler et al., 2009; Tenenhaus et al., 2005). The predictive relevance of the model for a specific endogenous construct is indicated by a Q^2 value greater than zero (Hair et al., 2007; Stone, 1974; Geiser, 1974). Conversely, a value below zero indicates no predictive significance (Shamueli et al., 2019). This study's Q^2 values of 0.207 and 0.166 are greater than zero. This implies that there is predictive value to the exogenous constructs in relation to the endogenous constructs. Q^2 yielded the outcome shown in Table 4.16.

Table 4. 16: Predictive Relevance (Blindfolding) Q^2

Construct	Q^2 (=1-SSE/SSO)	Predictive (Yes/No)
The acceptance of farmers to adopt SFT	0.207	Yes
Food Security	0.166	Yes

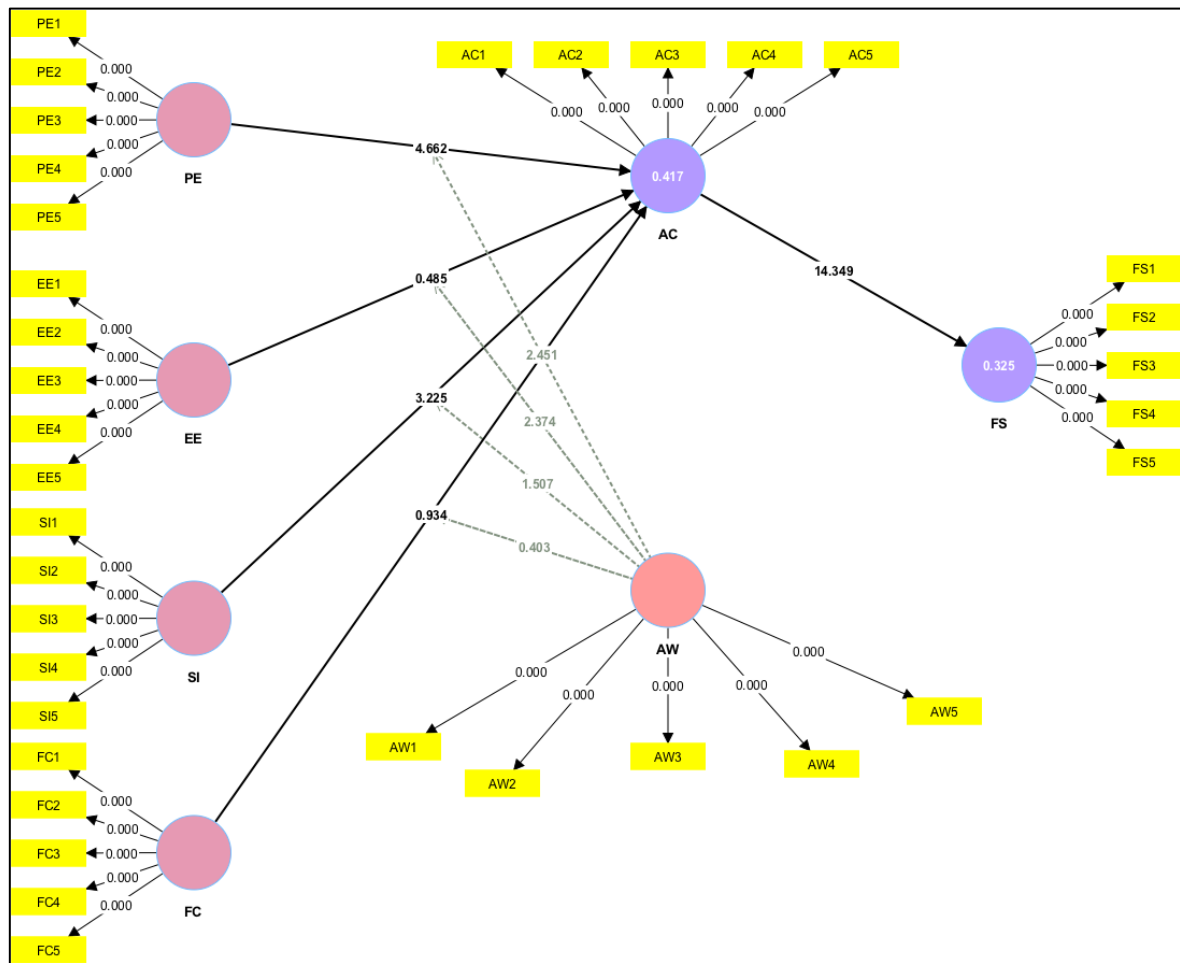


Figure 4. 4: Assessment of the Structural Model

4.13 Discussion of the Research Findings

This segment elucidates the coherence or lack thereof between the research outcomes and pertinent prior literature, while also offering justifications. In Sarawak, the purpose of this study was to determine the degree to which farmers would embrace the use of smart farming technologies to ensure food security. On the basis of the UTAUT, this study's conceptual framework was constructed, and technology awareness was suggested as a moderator to explain the acceptance of farmers to adopt SFT for the purpose of sustaining food security in Sarawak. The information was gathered from Sarawak-based farmers who

cultivate two categories of crops with exceptionally high yields: fruits and vegetables. Five divisions in Sarawak comprised the designated areas: Samarahan, Kapit, Serian, Kuching, and Sarikei. The respondents completed a questionnaire submission of 330 in total, of which 330 were deemed valid for data collection and were subsequently subjected to PLS-SEM analysis. In order to examine the data for missing values, anomalies, common method variance, and missing data on each variable, descriptive statistical reports were generated using SPSS. The research utilised PLS-SEM to evaluate the validity and dependability of the measurement and structural models.

The analysis from the data collection revealed the following notable findings:

H1: Performance expectancy has a positive relationship towards the acceptance of farmers to adopt SFT.

H2: Effort expectancy has a negative relationship towards the acceptance of farmers to adopt SFT.

H3: Social influence has a positive relationship towards the acceptance of farmers to adopt SFT.

H4: Facilitating conditions have a negative relationship towards the acceptance of farmers to adopt SFT.

H5a: Technology awareness moderates a positive relationship between performance expectancy and the acceptance of farmers to adopt SFT.

H5b: Technology awareness moderates a positive relationship between effort expectancy and the acceptance of farmers to adopt SFT.

H5c: Technology awareness does not moderates a relationship between social influence and the acceptance of farmers to adopt SFT.

H5d: Technology awareness does not moderate a relationship between facilitating conditions and the acceptance of farmers to adopt SFT.

H6: The acceptance of farmers to adopt SFT has a positive relationship towards sustaining food security in Sarawak.

As a result, all hypotheses were supported in this research except for H2, H4, H5c, and H5d.

Research Question 1: How does the performance expectancy affect the acceptance of farmers to adopt SFT?

The research objective of the study is to assess the effect of PE on the acceptance of farmers to adopt SFT. In accordance with UTAUT, the study hypothesizes that the user's perception of the technology or system dictates its suitability for implementation. The user's perceived ease of use (PE) regarding the system is a notable indicator of intention to use, which subsequently has a positive impact on the user's actual usage of the system. Additionally, PE assesses farmers' receptivity to smart farming technologies based on the extent to which SFT improves farmers' productivity, saves them time, increases in convenience, and improves their utility.

Hypotheses 1: *Performance expectancy has a positive relationship towards the acceptance of farmers to adopt SFT.* Through this study, it is determined that PE positively influences farmers' acceptance of SFT as one of the antecedents. This finding aligns with prior research that investigated the impact of PE on technology adoption intentions (Ronaghi & Forouharfar, 2020; Wei & Lim, 2022). It provides empirical support for the notion that PE can have a positive influence on technology adoption intentions. In addition to this, the integration of integrated pest management and precision agriculture, which are components of SFT, allows farmers to decrease their dependence on fertilisers and pesticides without sacrificing crop productivity. The results obtained in this investigation align with the

findings reported in the works of Ma and Abdulai (2018), Ali et al. (2018) and Wu (2022). which provides evidence that the adoption of CAPs results in enhanced sustainable agricultural performance. The results of the study provide further support for the claim that SFT has an enduring impact on the agricultural industry (FAO, 2018). Furthermore, as shown in Table 4.12, the acceptance of SFT by farmers is positively correlated with PE. This indicates that farmers who hold greater expectations regarding the impact of SFT on their performance are more likely to utilise SFT equipment and facilities on a regular basis. The analysis indicates that PE could influence the sustaining food security of the farmers in Sarawak.

Research Question 2: How does the effort expectancy affect the acceptance of farmers to adopt SFT?

The objective of this study is to examine the effect of effort expectancy on the acceptance of farmers to adopt SFT. UTAUT demonstrates that EE is a determinant of the intention and application of the system (Venkatesh et al., 2003).

Hypotheses 2: *Effort expectancy has a positive relationship towards the acceptance of farmers to adopt SFT.* In this research, EE is not identified as having a positive influence as one of the antecedents affecting the acceptance of farmers to adopt smart farming technologies. The study's findings are consistent with several studies that have shown an insignificant relationship between EE and the adoption of agricultural technologies (Schukat & Heisi, 2021). This study result is similar to previous studies' empirical findings (Li & Cheng, 2021), which revealed that EE negatively influences farmers' acceptance of SFT and sustaining food security. Ayaz and Yanartas (2019) reported similar results on effort expectancy being insignificant toward intention behavioural on the acceptance of electronic document management (EDMS).

Furthermore, the degree to which producers perceive the SFT complexity and convenience of use is reflected in EE. Consequently, this result suggests that EE is not a determining factor that can impact the farmers' inclination to embrace the SFT. One plausible explanation is that farmers in Sarawak are not acquainted with SFT and, as a result, lack a comprehensive understanding of their level of ease or difficulty of use. Due to this unfamiliarity, farmers might underestimate the amount of effort necessary to implement SFT. Therefore, if farmers consider the SFT to be user-friendly, intuitive, and adaptable, they are more likely to embrace the adoption of this innovative technology.

Research Question 3: How does the social influence affect the acceptance of farmers to adopt SFT?

The objective of this study is to identify the social influence effect on the acceptance of farmers to adopt SFT. Social influence (SI) has the potential to exert a positive impact on a user's intention to utilise a system, thereby exerting an influence on the user's behaviour (Venkatesh et al., 2003). Social influence (SI) pertains to the impact that the acceptance of farmers to adopt SFT is influenced by the expectations of other significant individuals in their vicinity, such as family members, colleagues, and acquaintances. As an illustration, a farmer might embrace SFT at the recommendation of their acquaintances.

Hypotheses 3: *Social influence has a positive relationship towards the acceptance of farmers to adopt SFT.* SI has been demonstrated to have a positive impact on the acceptance of farmers to adopt smart farming technologies. This finding is consistent with prior research that investigated the impact of SI on technology adoption intention (Ronaghi & Forouharfar, 2020; Wei & Lim, 2022; Sa'ari et al., 2018). It provides empirical evidence that SI might have a positive influence on technology adoption intention. The cultivators in Sarawak are primarily influenced by influential and important individuals. Furthermore, numerous

farmers are considerably influenced in their decision-making processes by family and friends (Foster & Rosenzweig, 1995; Schukat & Heise, 2021). Farmers may exhibit a higher propensity to embrace technology when they observe its successful implementation by others. Perceived risk and uncertainty can be mitigated by observing others utilise the technology. Another possibility is that farmers are more likely to adopt a technology if they believe it is important from their peers. This is because social norms can influence individual behaviour, and farmers may feel pressure to adopt a technology if they believe it is expected.

According to Beza et al. (2018), the acceptance of the Indian farmer on the IoT-A shows a positive influence by social influence because farmers interact with fellow villagers before deciding whether to adopt the technology. Farmers often rely on their communities to engage in discussions and exchange information regarding the challenges, benefits, and advantages associated with the adoption of new technologies that are unfamiliar to them.

Research Question 4: How does the facilitating conditions affect the acceptance of farmers to adopt SFT?

The objective of this study is to determine the effect of facilitating conditions on the acceptance of farmers to adopt SFT. FC may have a direct and positive impact on the utilisation of a system, according to the UTAUT (Venkatesh et al., 2003). FC is defined in this study as the organisational and technological resources that are accessible to SFT. Perceived accessibility refers to the degree to which an individual believes they have the essential knowledge, resources, and technical support to utilise the technology.

Hypotheses 4: Facilitating conditions have *a positive relationship towards the acceptance of farmers to adopt SFT*. The findings of this study unexpectedly validate that FC does not affect the acceptance of farmers to adopt SFT. Thus, the hypotheses regarding a direct correlation between FC and the acceptance of farmers to adopt SFT was refuted by

these findings. Moreover, the outcomes of prior investigations substantiate this discovery (Li & Cheng, 2021). A potential rationale for FC could be that farmers continue to believe that conventional farming is preferable to SFT, therefore unaware about SFT and lack internet access. To encourage the use of SFT by Sarawak's farmers, it is crucial to establish FC with respect to technological, human, and educational capacity.

Research Question 5: How does technology awareness moderate the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, and the acceptance of farmers to adopt SFT?

The objective of this study is to test the effect of technology awareness moderate the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions, and the acceptance of farmers to adopt SFT. Technology awareness is the degree to which an individual is familiar with a particular technology and its potential benefits. According to the UTAUT, it is a key factor in influencing individual technology acceptance. In SFT, technology awareness can be influenced by farmers' access to SFT information, education level, and engagement with other farmers and agricultural professionals.

Hypotheses 5a: *Technology awareness moderates a positive relationship between performance expectancy and the acceptance of farmers to adopt SFT.* In this study, awareness technology has a moderate effect on the relationship between PE and the acceptance of farmers adopting SFT to sustain food security in Sarawak. The statement that technology awareness has a positive moderated effect on the relationship between PE and the acceptance of farmers to adopt SFT in sustaining food security in Sarawak. However, a high AW relationship between PE and AC is become weaker as hypothesised in present study. The significance of the interaction term between performance expectancy and the

acceptance of farmers to adopt SFT proves that the relationship is moderated although the effect size is not very strong but it is expected in case of a complex model involving many variables. This is consistent with previous studies, which have shown that technology awareness moderated a relationship between performance expectancy and behavioural intention (Daniali et al., 2022; Abubakar & Ahmad, 2015). The finding shows that technology awareness can play a moderating role in the relationship between performance expectancy and the acceptance of SFT even though it is a weak relationship. However, it can become a stronger relationship if farmers are more aware of SFT are more likely to be aware of the potential benefits of these technologies and are, therefore, more likely to have positive expectations about them.

Hypotheses 5b: *Technology awareness moderates a positive relationship between effort expectancy and the acceptance of farmers to adopt SFT.* The result shows that technology awareness has a positive moderated effect on the relationship between EE and the acceptance of farmers to adopt SFT in sustaining food security in Sarawak is such higher technology awareness stronger this positive relationship as hypothesised in present study This is consistent with previous research, which has shown that technology awareness moderated a relationship between effort expectancy and the behavioural intention (Daniali et al., 2022; Abubakar & Ahmad, 2015). One possible explanation for this finding is that farmers with high technology awareness are more likely to be aware of the potential benefits of SFT, even if they are initially challenging to use. Additionally, farmers with high technology awareness may be more likely to seek out and use resources to help them learn how to manage SFT.

Hypotheses 5c: *Technology awareness moderates a positive relationship between social influence and the acceptance of farmers to adopt SFT.* The findings indicate that

technology awareness does not moderate effect on the relationship between social influence and the acceptance of farmers to adopt SFT in sustaining food security in Sarawak. The interaction term was found to be insignificant and thus no moderating effect was found. This is consistent with previous research, which has shown that technology awareness does not moderate a relationship between social influence and the behavioural intention (Abubakar & Ahmad, 2015). In addition, the result from the previous study also was inconsistent because of the limited studies focused on the technology awareness as a moderator. This implies that the correlation between social influence and SFT adoption is notably weak for farmers with a low level of technology awareness compared to farmers with a high level of technology awareness. Farmers confine themselves to their limited social network, exchanging knowledge exclusively inside their circle, relying on the expertise of others within that circle.

Hypotheses 5d: *Technology awareness moderates a positive relationship between facilitating conditions and the acceptance of farmers to adopt SFT.* The findings indicate that technology awareness does not moderate effect relationship between facilitating conditions and the acceptance of farmers to adopt SFT in sustaining food security in Sarawak. The interaction term was found to be insignificant and thus no moderating effect was found. This is consistent with previous study, which has shown that technology awareness does not moderate a relationship between social influence and the behavioural intention (Daniali et al., 2022; Abubakar & Ahmad, 2015). The assertion that technology awareness does not exert a moderating influence on the correlation between facilitating conditions and the acceptance of farmers to adopt SFT in sustaining food security in Sarawak implies that farmers' perceptions regarding the accessibility of resources and assistance remain unaffected by their level of awareness regarding SFT. This may be attributed to

several problems, including little understanding of SFT, inadequate infrastructure, limited internet connection, and a preference for traditional farming methods. Consequently, farmers may need more incentive to invest in SFT, irrespective of their knowledge about the technology.

Research Question 6: What is the impact on the acceptance of farmers to adopt SFT in sustaining food security?

The objective of this study is to investigate the impact of the acceptance of farmers to adopt SFT in sustaining food security in Sarawak. Smart farming technologies (SFT) are agricultural practices that aim to produce food while minimising environmental impact and conserving natural resources. SFT are essential for sustaining food security, as they can help to increase crop yields, reduce reliance on external inputs, and build resilience to climate change. The acceptance of farmers to adopt SFT is critical for their widespread adoption and for achieving the goal of sustainable food security. Several factors can influence farmer acceptance of SFT, including performance expectancy, effort expectancy, social influence, and facilitating conditions.

Hypotheses 6: *The acceptance of farmers to adopt SFT has a positive relationship towards sustaining food security in Sarawak.* The acceptance of farmers to adopt ST has been demonstrated to have a positive impact on the food security. Consequently, the higher the adoption rate of SFT among farmers, the more probable it is that food security in Sarawak will be maintained, thereby leading to an augmentation in crop productivity. This result is consistent with previous studies on post-harvest technologies and climate-smart agriculture, which can provide food availability to the country (Mutungi et al., 2023; Mwungu et al., 2018). SFT is specifically engineered to enhance agricultural productivity and mitigate the adverse environmental effects of agriculture. Furthermore, it is worth noting that increased

production levels are more financially helpful due to the economies of scale (Manda et al., 2015; Abdulai & Huffman, 2014; Gitonga et al., 2013). In addition, the imperative adoption of technologies is a critical factor in ensuring the maintenance of food security.

4.14 Summary

This chapter has presented a view of the evidence that supported the model's reliability, convergent validity, and discriminant validity and tested the formulated hypotheses. The findings from the analysis showed that out of nine hypotheses, five are supported; four are not supported. The next chapter discusses the research implications, recommendations for future study, limitations of the study, and conclusion.

CHAPTER 5

RECOMMENDATIONS AND CONCLUSION

5.1 Introduction

This chapter provides a concise overview of the study, summarising the important discoveries made in the preceding chapter. Subsequently, the chapter elucidates the theoretical and practical implications of the study. This chapter also includes a discussion of the limits of the study and provides recommendations for future investigations. It concludes with an overall summary.

5.2 Summary of Findings

Table 5.1 provides the outline of the recommended hypotheses, in which five (5) hypotheses (H1, H3, H6, H5a and H5b) are supported, and four (4) hypotheses (H2, H4, H5c and H5d) are unsupported. According to the findings of this study, two factors are identified; both PE, SI to have a positive effect on the acceptance among the farmers in Sarawak. Then, a moderator also moderated a positive relationship between PE, EE and the acceptance of farmers to adopt SFT. In addition, the impact of the acceptance of farmers to adopt SFT in sustaining food security also has a positive relationship.

Table 5. 1: Summary of the Results of Research Questions and Hypotheses

Research Question and Hypotheses Statement		Results
Research Question 1: How does the performance expectancy affect the acceptance of farmers to adopt SFT?		
H1	Performance expectancy has a positive relationship towards the acceptance of farmers to adopt SFT.	Supported
Research Question 2: How does the effort expectancy affect the acceptance of farmers to adopt SFT?		
H2	Effort expectancy has a positive relationship towards the acceptance of farmers to adopt SFT.	Not supported
Research Question 3: How does the social influence affect the acceptance of farmers to adopt SFT		

Table 5.1 (continue)		
H3	Social influence has a positive relationship towards the acceptance of farmers to adopt SFT.	Supported
Research Question 4: How does the facilitating conditions affect the acceptance of farmers to adopt SFT?		
H4	Facilitating conditions have a positive relationship towards the acceptance of farmers to adopt SFT.	Not supported
Research Question 5: Does technology moderate the relationship between performance expectancy, effort expectancy, social influence, facilitating conditions and the acceptance of farmers to adopt SFT?		
H5a	Technology awareness moderates a positive relationship between performance expectancy and the acceptance of farmers to adopt SFT	Moderation
H5b	Technology awareness moderates a positive relationship between effort expectancy and the acceptance of farmers to adopt SFT.	Moderation
H5c	Technology awareness moderates a positive relationship between social influence and the acceptance of farmers to adopt SFT.	No moderation
H5d	Technology awareness moderates a positive relationship between facilitating condition and the acceptance of farmers to adopt SFT	No moderation
Research Question 6: What is the impact on the acceptance of farmers to adopt SFT in sustaining food security?		
H6	The acceptance of farmers to adopt SFT has a positive relationship towards sustaining food security in Sarawak	Supported

5.3 Research Implications

This study is aimed to identify the factors influencing the acceptance of the farmers to adopt SFT in sustaining food security in Sarawak. Moreover, the study included the moderator effect, which is the technology awareness to test the effect on the PE, EE, SI, FC, and the acceptance of farmers to adopt SFT in sustaining food security.

Figure 5.1 demonstrates the potential of smart farming technology to enhance many facets of agricultural operations using the data obtained from technologies such as IoT. By providing data for optimising irrigation, fertilisation, and pest management, this technology may enable farmers to enhance their crop yields (Dhanaraju et al., 2022). In addition, with the surveillance of crop quality, farmers may promptly detect and resolve unwanted issues

and therefore may improve the calibre of their goods. Moreover, it can enhance farmers' productivity and cost-effectiveness by leveraging automated processes and data analysis to facilitate well-informed decision-making (Javaid et al., 2022). In addition, the technology has the potential to promote sustainability. For example, with the implementation of precision agricultural techniques, farmers may minimise their reliance on water, pesticides, and fertilisers, thus contributing to environmental conservation.

Smart farming is an agricultural approach that uses technology to gather data on crops and the surrounding environment, enabling better-informed decision-making on farm management (Javaid et al., 2022). These activities encompass utilising sensors to track soil moisture and nutrient levels, employing drones to capture aerial photographs of crops for pest and disease identification, and utilising robots to automate operations like weeding and harvesting. Furthermore, artificial intelligence (AI) may be employed to analyse and compute data obtained from sensors and various sources in order to detect patterns and trends. These findings can then be utilised to forecast crop yields and other relevant variables.

Although still in its nascent phase, smart farming has the capacity to fundamentally transform agricultural practices. Through the utilisation of data collection and analysis technology, farmers may enhance their decision-making process for farm management, resulting in amplified crop yields, enhanced product quality, and heightened operational efficiency. However, these efforts need interventions and regulations from the government and policymakers, therefore it may impart sustainable food security. The theoretical implications and practical implications will be discussed next.

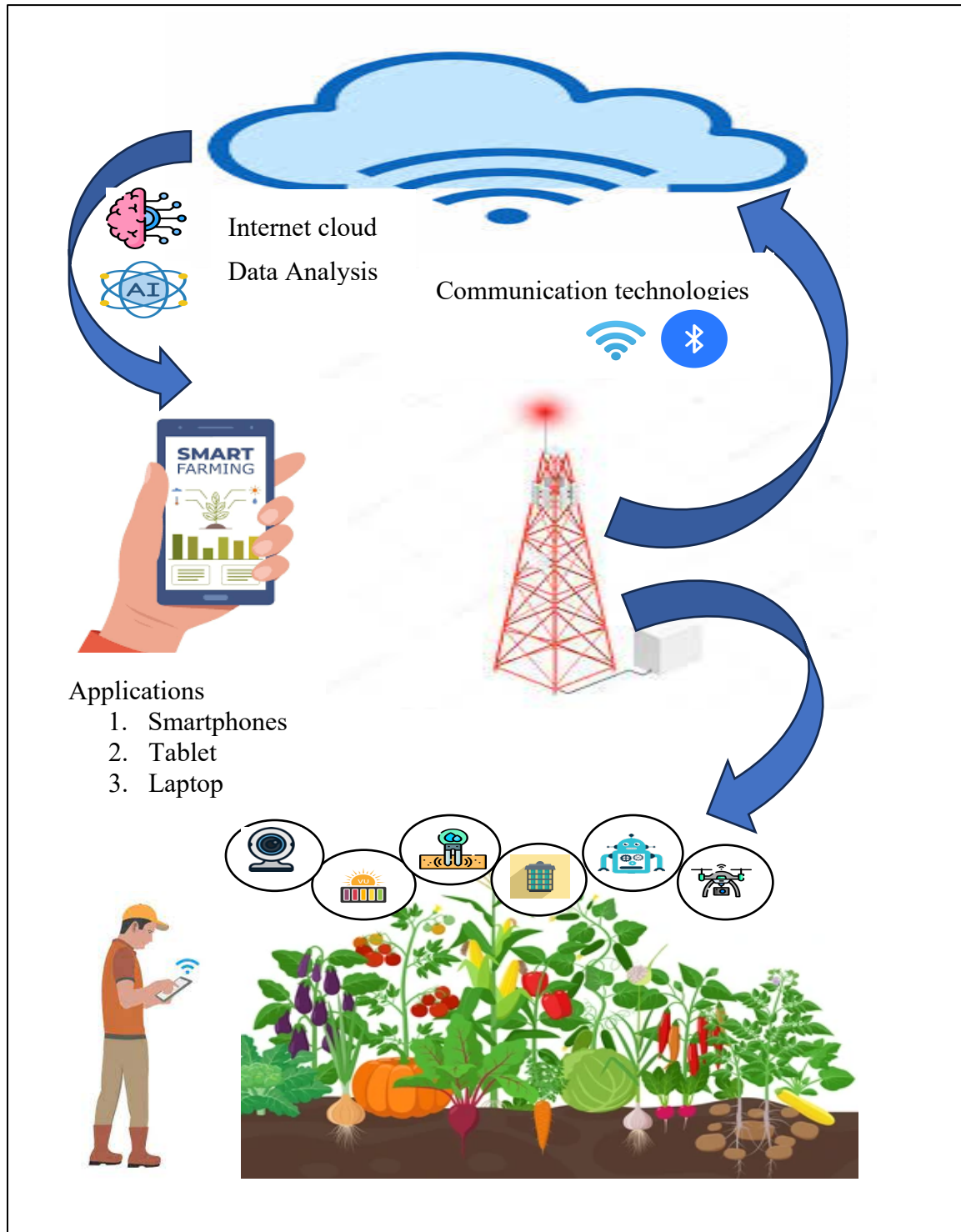


Figure 5. 1: Smart Farming Technologies

5.3.1 Theoretical Implications

This study is focused on examining the theoretical and empirical studies of the acceptance of farmers to adopt SFT in sustaining food security in Sarawak. There needs to be more empirical research dedicated to study on the acceptance of farmers to adopt new technology. Most farmers need to gain familiarity with smart agriculture technology due to their unusual and recent introduction to the business. Besides, it substantially impacts farmers and the maintenance of food security in Sarawak. Therefore, the study's framework enhances comprehension of the factors that influence farmers' acceptability of adopting SFT to ensure food security in Sarawak. The study's findings demonstrate a positive correlation between PE and SI. Remarkably, the results of EE and FC are inconsequential, contradicting the previous study's findings. Additionally, the study has specifically discovered a strong positive correlation between PE and SI and the acceptance of farmers to adopt SFT. The results align with the UTAUT model, which proposes that these characteristics are crucial in determining technology adoption. The study also has determined that there is no significant correlation between EE and FC with the acceptance of farmers to adopt SFT. These findings also enhance the UTAUT model by offering empirical proof to substantiate the fundamental components of the model. Thus, this study establishes a foundation for other fellow researchers and academics to investigate the farmers' acceptance to adopt SFT in sustaining food security. It also encourages future exploration of the interconnections between these concepts, particularly within the agricultural field.

Furthermore, this study incorporates technology awareness as a moderator to gauge the acceptance of farmers to adopt SFT. Technology awareness is seldom utilised as a moderator in UTAUT, particularly in scholarly literature about agricultural activities. In this study found that technology awareness has a moderating role in the link between PE, EE,

and the acceptance of farmers to adopt SFT. However, technology awareness has not acted as a moderating factor in the relationship between SI, FC, and the acceptance of farmers to adopt SFT.

In addition, previous literature research revealed a limited number of studies that investigate the role of technology awareness as a moderator within a construct (Daniali et al., 2022; Abubakar & Ahmad, 2015). Furthermore, the level of technology awareness among farmers significantly indicates their adoption of technology (Ullah et al., 2020). Prior research on m-commerce has explored the concept of technology awareness as a moderate construct, as evidenced by studies conducted by Abubakar and Ahmad (2013) and Omar (2011). Additionally, Daniali et al. (2021) investigated the behavioural intentions to utilise 4.5G mobile technologies.

This study establishes a conceptual basis for the significance of PE, EE, SI, FC and technology awareness as factors that influence the acceptance of farmers to adopt SFT. Furthermore, it has improved our comprehension of the factors that influence the acceptance of farmers to adopt SFT, leading to a more thorough understanding of farmers' willingness to embrace SFT for sustainable food security. Hence, the study's findings enhance the UTAUT model by offering empirical proof that validates the fundamental components of the model.

5.3.2 Practical Implications

The study's findings offer the government, policymakers, farmers, and stakeholders an opportunity to gain access to valuable practical insights. Initially, it is crucial to educate farmers in Sarawak about the importance of food security sustenance in order to encourage their acceptance of adopting SFT for sustainable food security. The study results indicate a significant relationship between PE and SI on the acceptance of farmers to adopt SFT.

Nevertheless, there is an insignificant relationship between EE and FC on the acceptance of farmers to adopt SFT.

Furthermore, policymakers and the government ought to prioritise their focal point on performance expectancy of the SFT to enhance the pace of adoption. It is expected that the inclination to adopt is greater when SFT is shown to offer additional features or capabilities that facilitate the performance of everyday chores, hence benefiting the farmers' way of life. For instance, the SFT user-friendliness may encourage farmers to access and comprehend the SFT more quickly. The farmers in this study believed that SFT may expedite their duties and enhance their revenue by producing a more incredible amount and higher quality crop. Hence, PE of the SFT plays a pivotal role in determining the extent to which the technology is embraced on a large scale.

Dismally, the majority of farmers in Sarawak have a limited degree of education. However, they do demonstrate the willingness to acquire new knowledge and embrace advancements in agricultural technology. Besides, it has been found that effort expectancy has little effect on farmers' willingness to adopt SFT. Additionally, the design of SFT is highly complex and challenging for farmers to understand. Furthermore, the government and policymakers must evaluate the functioning and structure of SFT very carefully. This may contribute to the proliferation of farmers using the SFT in the future.

Conversely, the government may enhance farmers' acceptance to adopt SFT by augmenting their understanding of SFT adoption and its contribution to sustainable food security. The government may arrange seminars and training sessions to prepare farmers on the adoption, development, and effect of SFT in agriculture. Additionally, they can guide farmers using SFT infrastructure to enhance their understanding of SFT. Hence, farmers who are committed and enthusiastic about implementing SFT should be more aware of the

significance of embracing the adoption of SFT in ensuring food security. Social interactions and conventions can positively pressure farmers, motivating them to adopt SFT. The opinions expressed by friends, family, and superiors may significantly impact farmers. Thus, social influence serves as one of the primary precursors in the adoption of technology.

Although it is found that facilitating conditions does not influence farmer's acceptance to adopt SFT, both the Federal Government and Sarawak State Government ought to expedite the construction of essential infrastructure, to ensure access to high-speed internet, impart fundamental knowledge, offer SFT support, and provide more exposure to SFT for farmers. To enhance the acceptance of farmers to adopt SFT, the government should provide improved facilities and suitable infrastructure. This approach corresponds with the aims of the Sarawak digital economy strategy and addresses the farmers' requirements for adopting SFT.

Furthermore, the role of technology awareness as a moderator in this study is to regulate the connection between PE, EE, SI, FC, and the acceptance of farmers to adopt SFT. This moderation helps to offer the government and policymakers a more precise understanding of when farmers in Sarawak are prepared to transition to a digital lifestyle and are open to embracing this lifestyle, mainly when their level of technology awareness is high. Similarly, the investigation of technology awareness in this study has a great significance to the Sarawak government, policymakers, stakeholders, and farmers. As technology awareness increases, Sarawak farmers will enhance their living standards and carry out chores more effectively with the assistance of digital technology.

Additionally, the government should contemplate initiatives to promote the advantages of digital technologies and demonstrate agricultural technology utilised in other nations to reach farmers with poor agricultural welfare. One approach is to establish demonstration

farms or provide successful case studies in Sarawak that highlight the concrete advantages and good results obtained from the adoption of smart agricultural technology. Such practical experience can significantly impact farmers' perspectives and promote the adoption of new practices.

In addition, the government should implement extensive training programs and awareness campaigns on smart agricultural technology for farmers, utilising mass media platforms like radio and television. The issue is the need for more professional and precise information and awareness about SFT among farmers in Sarawak, which are crucial for maintaining food security.

The government and policymakers should also prioritise the provision of financial assistance and incentives to encourage farmers to use smart agricultural technology. The primary obstacle farmers face in adopting SFT is their inability to finance its high investment cost. Financial assistance, subsidies, or incentives can help farmers get and adopt smart agricultural technologies. This may entail the provision of government grants, low-interest loans, or subsidies to facilitate the acquisition of equipment, hence enhancing the accessibility and affordability of these technologies.

Furthermore, the availability of knowledge and assistance is crucial for enhancing technology awareness among farmers. Therefore, the government may provide a platform that facilitates farmers' access to information, resolution of problems, and acquisition of assistance about the implementation and incorporation of smart farming technology into their agricultural activities. This platform may facilitate the enhancement of farmers' knowledge, awareness, and mutual assistance in the adoption and implementation of these technologies according to their requirements.

Another favourable result from this study is that the government and policymakers should notice and understand the factors influencing farmers' acceptance to adopt SFT in sustaining food security in Sarawak. The government and policymakers may utilise the documented outcomes of PE, EE, SI, FC, and technology awareness as a framework to develop more effective agriculture policies. This study may help to attain sustainable food security and ultimately yield advantages for all stakeholders and farmers in the agriculture industry. Therefore, enhancing the acceptance of farmers to adopt SFT will be crucial in attaining sustainable food security, economic advancement, and productivity in Sarawak.

5.4 Limitations of the Study

The study on the acceptance of farmers to adopt SFT in sustaining food security in Sarawak is initially hindered by a limited time frame, which has posed significant difficulties, particularly in data acquisition, analysis, and the extent of the investigation. The collection of a comprehensive range of perspectives and experiences is impeded by time constraints, which has led to a reduced or less varied sample size. Time limitations complicate comprehensive analyses, resulting in hasty processing of gathered data that has inadvertently disregarded subtle patterns and insights. In addition, the constrained duration hinders the implementation of methodological rigour comprehensive literature review, and meticulous writing and revision procedures, which may compromise the results' dependability, profundity, and overall calibre. To surmount these obstacles, it is imperative to implement effective time management techniques, engage in meticulous preparation, recognise the study's constraints, and suggest directions for future research that accommodate extended time frames.

Moreover, according to Bhattacharjee and Premkumar (2004), the influence of the UTAUT model's components will fluctuate over time, leading to many behavioural consequences. A cross-sectional investigation, including the one employed in this study, encounters challenges in establishing causality between predictors and outcomes (Carlson & Morrison, 2009). This is because the analysis is limited to a single moment (Chiu et al., 2010).

Additionally, an important constraint highlighted in this study is the absence of governmental influences accounted for in the model. After conducting observations and engaging in discussions with farmers during the data collection phase, it is evident that governmental support, strategic initiatives, and the prevailing political climate significantly impact the level of acceptability among farmers.

Furthermore, the study's scope is restricted to particular regions renowned for their vegetable and fruit cultivation due to geographical limitations. This may have resulted in the exclusion of farmers engaged in various agricultural activities or operating in diverse geographical areas within Sarawak. Consequently, the study's results may not comprehensively reflect the varied viewpoints, operational strategies, obstacles, and levels of acceptability towards technology among farmers engaged in different crop varieties or conducting business in different regions of Sarawak. The generalizability of the findings is limited by this constraint, as the perspectives and experiences of farmers cultivating various commodities in other geographic areas may have been substantially dissimilar to those investigated in the research.

5.5 Recommendation for a Future Study

Future study should employ the UTAUT2 paradigm to investigate the adoption of Smart Farming Technologies among Sarawak farmers has excellent. UTAUT2, an expansion of the initial UTAUT model, includes other elements such as hedonic motivation, price value, habit, and enabling situations, providing a more thorough comprehension of technology adoption behaviours. The application of UTAUT2 in future studies can provide a more comprehensive investigation into the intricate elements that impact farmers' intentions and actual adoption of SFT. Through the analysis of factors such as hedonic motivation (the enjoyment obtained from using the technology) and habit (the automatic response towards technology usage), researchers may get valuable insights into the emotional and habitual factors that influence adoption, which may be of great importance in agricultural situations. Furthermore, taking into account factors such as price value (the perceived value of the technology in proportion to its cost) may provide insights into the economic factors that influence farmers' decisions to adopt it. The employment of UTAUT2 in future research will offer a more inclusive framework for examining the various factors that influence technology adoption behaviours among farmers in Sarawak. This will enhance our understanding of the dynamics of adoption and enable more precise interventions or strategies to promote the adoption of technology in agriculture.

Moreover, it is crucial to prioritise longitudinal studies in future research on the adoption of SFT among Sarawak farmers to gain a thorough knowledge of the adoption process. Longitudinal studies, which monitor changes over time, allow researchers to identify cause-and-effect correlations, study the development of attitudes and behaviours, and analyse the effects of policies or interventions on the adoption of technology. These studies provide valuable insights into long-term technology adoption by considering the

changing nature of adoption journeys and accounting for temporal variability. This information can help policymakers develop more successful and sustainable policies. Implementation of longitudinal research entails gathering data from a consistent group of farmers over a prolonged duration, which allows for a more comprehensive comprehension of how intentions and behaviours regarding technology adoption will develop over time in response to different causes.

In addition, this research is reproducible and may be used on more expanded geographical scope. It encompasses various agricultural environments, possibly including a more comprehensive array of viewpoints, practices, and contextual variables that impact the adoption of technology among farmers in Sarawak. The link between independent factors (such as PE, EE, SI, and FC) and technology adoption intents or behaviours may be influenced by each location's distinct socio-economic, environmental, and infrastructural aspects. Factors such as diverse agricultural techniques, resource availability, government assistance, and market conditions may vary between locations, resulting in different levels of influence on farmers' acceptance of SFT. The expanded scope of future study enables a more detailed analysis, offering insights into the varying interactions of these independent variables in diverse regions. This contributes to a more comprehensive understanding of the factors that influence technology adoption behaviours for food security sustenance in Sarawak.

Finally, further study should prioritise the investigation of the various dimensions of governmental influence, assessment of the efficacy of specific policies and initiatives, and study on the experiences and perspectives of farmers about these endeavours. This thorough examination will enhance comprehension of how governmental considerations profoundly influence the implementation of SFT and may provide valuable insights to policymakers in

formulating more efficient ways to encourage technology adoption among farmers in Sarawak.

5.6 Conclusion

This study identifies the factors that influence the acceptance of farmers to adopt SFT in sustaining food security in Sarawak. Data for this study is gathered through the administration of a questionnaire survey to achieve the research objectives. In addition to nine hypotheses and six research questions, the conceptual framework for this investigation is also formulated. It is determined that five of the nine hypotheses in the research model are significant in the context of this study.

Additionally, this study shows results obtained suggest that the implementation of SFT and the impact of the farmers' consent to embrace the SFT in sustaining food security in Sarawak have been significantly influenced by SI and PE. It is important to note that the relationship between PE, EE, and the acceptance of farmers to adopt SFT is substantially moderated by technology awareness. In addition, to improve the economy and agriculture sector of Sarawak, the government and its respective organisations must collaborate to support farmers in the modernisation process as the government expands its incorporation of technological advancements. Overall, it is anticipated that the outcomes of this study will be advantageous to the Government of Sarawak, stakeholders, legislators, researchers, academics and farmers in the agricultural sector by facilitating the identification of farmers' requirements and the advancement of technology that is appropriate for the environment. Ultimately, it is likely that Sarawak will implement strategies to achieve sustainable food security through technological advancement and become a net food exporter by 2030, thereby contributing to economic development.

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APPENDICES 1: QUESTIONNAIRES

ACADEMIC SURVEY



**Department of Business and Management, Faculty of
Economic and Business, Universiti Malaysia Sarawak, 94300,
Kota Samarahan, Sarawak, Malaysia.**

Subject: An academic survey related to the acceptance of farmers to adopt smart farming technologies in sustaining food security in Sarawak.

Main objective: To identify factor influencing the acceptance of farmers to adopt smart farming technology in sustaining food security in Sarawak.

Dear Respondent,

I am a Doctor of Business Administration (DBA) candidate, conducting a research on "Factor Influencing the Adoption of Smart Farming Technology: The Role of Technology Awareness as Moderator".

In order to successfully complete my doctorate degree, I would like to invite you to participate in this survey. This research is very important for me and for the agriculture sector in order to increase the adoption of smart farming technologies in sustaining food security. Furthermore, I would encourage you to please take some time out of your busy schedule to complete this survey.

The accuracy of how you feel about the statement is very crucial for my study. I guarantee your answer and responses will be kept strictly confidential and will be used for academic purpose only.

For more information, please contact me at 012-8118779 (Sharon Notiazila binti Ali) or email me at notiazila.ali@gmail.com.

Thank you for your cooperation.

Best Regards,

Sharon Notiazila binti Ali

Subjek: Satu kajian akademik berkaitan penerimaan petani untuk penggunaan teknologi pertanian pintar dalam mengekalkan keterjaminan makanan di Sarawak.

Objektif utama: Untuk mengenalpasti faktor mempengaruhi penerimaan petani dalam penggunaan teknologi pertanian pintar.

Responden yang dihormati,

Saya ialah calon Doktor Pengurusan Perniagaan (DBA) yang sedang menjalankan penyelidikan tentang "Faktor yang Mempengaruhi Penggunaan Teknologi Pertanian Pintar: Peranan Kesedaran Teknologi sebagai Moderator".

Bagi menyelesaikan ijazah kedoktoran saya dengan berjaya, saya ingin menjemput anda sebagai petani untuk mengambil bahagian dalam kaji selidik ini. Penyelidikan ini amat penting bagi saya dan sektor pertanian untuk meningkatkan penggunaan teknologi pertanian pintar dalam mengekalkan jaminan makanan. Justeru, saya menggalakkan anda untuk meluangkan sedikit masa daripada jadual sibuk anda untuk melengkapkan kaji selidik ini.

Ketepatan perasaan anda terhadap pernyataan ini sangat penting bagi kajian saya. Saya jamin jawapan dan maklum balas anda akan dijaga secara rahsia dan hanya akan digunakan untuk tujuan akademik sahaja.

Untuk maklumat lanjut, sila hubungi saya di 012-8118779 (Sharon Notiazila binti Ali) atau e-mel saya di notiazila.ali@gmail.com

Terima kasih atas kerjasama anda.

Yang benar,
Sharon Notiazila binti Ali

Preliminary Questions/Soalan Pendahuluan

1. Are you a farmer residing in Sarawak?
Adakah anda seorang petani yang tinggal di Sarawak?

Yes/ Ya ☐
No/ Tidak ☐

If you answer Yes, then go to question 2 / Jika jawapan anda Ya, sila jawapan soalan 2

2. Type of crops/ Jenis tanaman
Vegetable/Sayur (eg: Leafy vegetables, Chillies, Tomatoes and etc /
Sayur berdaun, Cili, Tomato, Kobis dan lain-lain) ☐
Fruit / Buah (eg: Golden melon, watermelon, and etc/
Tembikai emas, tembikai dan lain-lain) ☐
None of the above / Tiada satu pun di atas ☐

If you answer "Vegetable" or "Fruit", then proceed to the next section

Jika jawapan anda "Sayur" atau "Buah", sila teruskan ke bahagian seterusnya

Section 1 / Bahagian 1

Demographic information / Maklumat Demografik

Please place (✓) in the block that relates to you.

Sila tanda (✓) dalam kotak yang berkaitan dengan anda.

- | | | | |
|---|--------------------------|-------------------------------------|--------------------------|
| 3. Age/ Umur | | 9. Marital Status/Status Pernikahan | |
| Less than 20 years old/ <i>Kurang daripada 20 tahun</i> | ☐ | | |
| 20 -29 years old / <i>20-29 tahun</i> | ☐ | Single/ <i>Bujang</i> | ☐ |
| 30-39 years old / <i>30 - 39 tahun</i> | ☐ | Married/ <i>Berkahwin</i> | ☐ |
| 40- 49 years old / <i>40 - 49 tahun</i> | ☐ | Others/ <i>Lain-lain</i> | ☐ |
| 50-59 years old / <i>50 - 59 tahun</i> | ☐ | | |
| 60 ears and above / <i>60 tahun dan ke atas</i> | ☐ | | |
| 4. Gender/ <i>Jantina</i> | | | |
| Male / <i>Lelaki</i> | ☐ | | |
| Female/ <i>Perempuan</i> | ☐ | | |
| 5. Ethnicity/ <i>Etnik</i> | | | |
| Malay / <i>Melayu</i> | ☐ | | |
| Iban / <i>Iban</i> | ☐ | | |
| Chinese / <i>Cina</i> | ☐ | | |
| Bidayuh/ <i>Bidayuh</i> | ☐ | | |
| Others/ <i>Lain-lain</i> | ☐ | | |
| 6. Years of farming experience/ <i>Bilangan tahun dalam pertanian</i> | | | |
| 1 – 10 years/ <i>1 -10 tahun</i> | ☐ | | |
| 11- 20 years/ <i>11 – 20 tahun</i> | ☐ | | |
| 21 – 30 years/ <i>21 – 30 tahun</i> | ☐ | | |
| 31 – 40 years/ <i>31 – 40 tahun</i> | ☐ | | |
| 40 years and above/ <i>40 tahun dan ke atas</i> | ☐ | | |
| 7. Level of education/ <i>Tahap Pendidikan</i> | | | |
| No formal education / <i>Tiada Pendidikan formal</i> | | ☐ | |
| Primary school / <i>Sekolah rendah</i> | | ☐ | |
| Secondary school / <i>Sekolah menengah</i> | | ☐ | |
| Certificate/ <i>Sijil</i> | | ☐ | |
| Diploma/ <i>Diploma</i> | | ☐ | |
| University degree and above / <i>Ijazah universiti dan ke atas</i> | | ☐ | |
| Others / <i>Lain-lain</i> | | ☐ | |
| 8. Monthly Income/ <i>Pendapatan bulanan</i> | | | |
| Below RM1500 / <i>Kurang daripada RM1500</i> | ☐ | | |
| RM1500 – RM3500 | ☐ | | |
| RM3500 – RM5500 | ☐ | | |
| RM5500 – RM8500 | ☐ | | |
| RM8500 and above / <i>Lebih daripada RM8500</i> | ☐ | | |

Section 2: Factor influencing the acceptance of farmers to adopt smart farming technologies.
Bahagian 2: Faktor-faktor mempengaruhi penerimaan petani dalam penggunaan teknologi pertanian pintar.

This section asks for your opinion regarding the adoption smart farming technologies. Please indicate to which extent do you agree or disagree with statement below using a 7 – points Likert scale as follow:

(1)= Strongly disagree ; (2) = Disagree ; (3) = Somewhat disagree ; (4) = Neutral ; (5) = Somewhat agree ; (6) = Agree ; (7) = Strongly agree

Bahagian ini meminta pendapat anda mengenai teknologi pertanian pintar. Sila bulatkan sejauh mana anda bersetuju atau tidak bersetuju dengan setiap pernyataan di bawah menggunakan skala Likert 7-mata seperti berikut:

(1)= Sangat tidak setuju ; (2)= Tidak setuju ; (3) = Agak tidak setuju ; (4) = Neutral ; (5) = Agak setuju ; (6) = Setuju ; (7) = Sangat setuju

No.	Performance expectancy <i>Jangkaan prestasi</i>							
1.	Using the smart farming technologies will useful in doing my farm activities. <i>Menggunakan teknologi pertanian pintar ini akan berguna dalam menjalankan aktiviti ladang saya.</i>	1	2	3	4	5	6	7
2.	Using the smart farming technologies will help me to accomplish my tasks more quickly than before in the farm. <i>Menggunakan teknologi pertanian pintar ini akan membantu saya menyelesaikan tugas dengan lebih cepat daripada sebelumnya di ladang.</i>	1	2	3	4	5	6	7
3.	Using the smart farming technologies will increase my chances of achieving higher crop productivity. <i>Menggunakan teknologi pertanian pintar ini akan meningkatkan peluang saya untuk mencapai produktiviti tanaman yang lebih tinggi.</i>	1	2	3	4	5	6	7
4.	Using smart farming technologies will increase my chances of increasing my income. <i>Menggunakan teknologi pertanian pintar ini akan meningkatkan peluang saya untuk meningkatkan pendapatan saya.</i>	1	2	3	4	5	6	7
5.	Using smart farming technologies will reduce the use of fertilizers, pesticides, and labour costs. <i>Menggunakan teknologi pertanian pintar ini akan mengurangkan penggunaan baja, racun perosak, dan kos tenaga kerja.</i>	1	2	3	4	5	6	7

No.	Effort expectancy <i>Jangkaan usaha</i>							
1.	Learning how to use the smart farming technologies is easy for me. <i>Mempelajari cara menggunakan teknologi pertanian pintar adalah mudah bagi saya.</i>	1	2	3	4	5	6	7
2.	My first impression of the smart farming technologies could be described as clear, favourable and comprehensive. <i>Tanggapan pertama saya terhadap teknologi pertanian pintar dapat digambarkan sebagai jelas, menguntungkan, dan komprehensif</i>	1	2	3	4	5	6	7
3.	I would find the smart farming technologies easy to use. <i>Saya dapati teknologi pertanian pintar mudah digunakan.</i>	1	2	3	4	5	6	7
4.	It is applicable to me become a skillful and deft user of the smart farming technologies. <i>Ia boleh menjadikan saya seorang pengguna teknologi pertanian pintar yang mahir dan cekap.</i>	1	2	3	4	5	6	7
5.	It would be easy for me to operate smart farming technologies. <i>Mudah bagi saya untuk mengendalikan teknologi pertanian pintar.</i>	1	2	3	4	5	6	7

No.	Social Influence <i>Pengaruh Sosial</i>							
1.	The people who are important to me think that I should use the smart farming technologies. <i>Orang-orang yang penting bagi saya berpendapat bahawa saya sepatutnya menggunakan teknologi pertanian pintar.</i>	1	2	3	4	5	6	7
2.	The people who have influence on my behaviour, think that I should use the smart farming technologies. <i>Orang-orang yang mempengaruhi tingkah laku saya berpendapat bahawa saya sepatutnya menggunakan teknologi pertanian pintar.</i>	1	2	3	4	5	6	7
3.	The people whose opinions are valuable to me prefer to use smart farming technologies.	1	2	3	4	5	6	7

	<i>Orang-orang yang pendapat mereka berharga bagi saya lebih suka menggunakan teknologi pertanian pintar.</i>							
4.	My near relatives, friends, and acquaintances are using the smart farming technologies themselves. <i>Sanak saudara, rakan-rakan, dan kenalan rapat saya sendiri menggunakan teknologi pertanian pintar.</i>	1	2	3	4	5	6	7
5.	The social media platform influence me to use smart farming technologies. <i>Platform media sosial mempengaruhi saya untuk menggunakan teknologi pertanian pintar</i>	1	2	3	4	5	6	7

No.	Facilitating conditions <i>Keadaan Memudahkan</i>							
1.	I have necessary facilities for using smart farming technologies relevant to farming. <i>Saya mempunyai kemudahan yang diperlukan untuk menggunakan teknologi pertanian pintar yang berkaitan dengan pertanian.</i>	1	2	3	4	5	6	7
2.	I have a basic knowledge on how to use smart farming technologies. <i>Saya mempunyai pengetahuan asas tentang cara menggunakan teknologi pertanian pintar.</i>	1	2	3	4	5	6	7
3.	I can get help from others when I have difficulties in using smart farming technologies. <i>Saya boleh mendapatkan bantuan daripada orang lain apabila saya menghadapi kesulitan dalam menggunakan teknologi pertanian pintar.</i>	1	2	3	4	5	6	7
4.	The internet access is available on the whole farm area. <i>Akses internet tersedia di seluruh kawasan ladang.</i>	1	2	3	4	5	6	7
5.	The smart farming technologies are more compatible as compared to traditional farming. <i>Teknologi pertanian pintar adalah lebih bersesuaian berbanding dengan pertanian tradisional.</i>	1	2	3	4	5	6	7

Section 3: Impacts of technology awareness as a moderator between of performance expectancy, effort expectancy, social influence, facilitating condition and the acceptances of farmers to adopt smart farming technologies.

Bahagian 3: Kesan moderator kesedaran teknologi terhadap hubungan jangkaan prestasi, jangkaan usaha, pengaruh sosial, keadaan memudahkan, dan penerimaan petani dalam penggunaan Teknologi Pertanian Pintar

We are interested in your views on how technology influences your life. Please indicate to which extent do you agree or disagree with statement below using a 7 – points Likert scale as follow:

(1)= Strongly disagree ; (2) = Disagree ; (3) = Somewhat disagree ; (4) = Neutral ; (5) = Somewhat agree ; (6) = Agree ; (7) = Strongly agree

Bahagian ini meminta pendapat anda mengenai teknologi pertanian pintar. Sila bulatkan sejauh mana anda bersetuju atau tidak bersetuju dengan setiap pernyataan di bawah menggunakan skala Likert 7-mata seperti berikut:

(1)= Sangat tidak setuju ; (2)= Tidak setuju ; (3) = Agak tidak setuju ; (4) = Neutral ; (5) = Agak setuju ; (6) = Setuju ; (7) = Sangat setuju

No.	Technology Awareness <i>Kesedaran teknologi</i>							
1.	<i>I follow the news about the smart farming technologies. Saya mengikuti berita tentang teknologi pertanian pintar.</i>	1	2	3	4	5	6	7
2.	<i>I follow the developments of the smart farming technologies. Saya mengikuti perkembangan teknologi pertanian pintar.</i>	1	2	3	4	5	6	7
3.	<i>I discuss with friends and people around me on issues about smart farming technologies usage. Saya berbincang dengan rakan-rakan dan orang di sekeliling saya tentang isu penggunaan teknologi pertanian pintar.</i>	1	2	3	4	5	6	7
4.	<i>I read about the problems of smart farming technologies usage. Saya membaca tentang masalah-masalah penggunaan teknologi pertanian pintar.</i>	1	2	3	4	5	6	7
5.	<i>I am aware on the advantage of smart farming technologies. Saya sedar akan kelebihan teknologi pertanian pintar.</i>	1	2	3	4	5	6	7

Section 4: The acceptance of farmers to adopt smart farming technologies

Bahagian 4: Penerimaan petani dalam penggunaan teknologi pertanian pintar.

This section asks for your opinion regarding the acceptance of farmers towards adoption of smart farming technologies. Please indicate to which extent do you agree or disagree with statement below using a 7 – points Likert scale as follow:

(1)= Strongly disagree ; (2) = Disagree ; (3) = Somewhat disagree ; (4) = Neutral ; (5) = Somewhat agree ; (6) = Agree ; (7) = Strongly agree

Bahagian ini meminta pendapat anda mengenai teknologi pertanian pintar. Sila bulatkan sejauh mana anda bersetuju atau tidak bersetuju dengan setiap pernyataan di bawah menggunakan skala Likert 7-mata seperti berikut:

(1)= Sangat tidak setuju ; (2)= Tidak setuju ; (3) = Agak tidak setuju ; (4) = Neutral ; (5) = Agak setuju ; (6) = Setuju ; (7) = Sangat setuju

No.	Acceptance of farmers to adopt smart farming technologies. <i>Penerimaan petani dalam penggunaan teknologi pertanian pintar</i>							
1.	I will accept smart farming technologies if it cheap and profitable. <i>Saya akan menerima teknologi pertanian pintar jika ia murah dan menguntungkan.</i>	1	2	3	4	5	6	7
2.	I will accept smart farming technologies if spare parts easy to obtain. <i>Saya akan terima alat ganti teknologi pertanian pintar jika ia mudah diperolehi.</i>	1	2	3	4	5	6	7
3.	If crops yields can increase, I have no hesitation in accepting smart farming technologies. <i>Jika hasil tanaman dapat meningkat, saya tidak ragu untuk menerima teknologi pertanian pintar.</i>	1	2	3	4	5	6	7
4.	The introduction of smart farming technologies should be able to increase my income. <i>Teknologi pertanian pintar yang diperkenalkan sepatutnya dapat meningkatkan pendapatan saya.</i>	1	2	3	4	5	6	7
5.	I will accept smart farming technologies if it can reduce production cost. <i>Saya akan menerima teknologi pertanian pintar jika ia dapat mengurangkan kos pengeluaran.</i>	1	2	3	4	5	6	7

Section 5 : Impacts of the acceptance of farmers to adopt smart farming technologies in sustaining food security

Bahagian 5: Kesan penerimaan petani dalam penggunaan teknologi pintar bagi mengekalkan keterjaminan makanan

We are interested in your views on the acceptance of farmers to adopt smart farming technologies effect in sustaining food security. Please indicate to which extent do you agree or disagree with statement below using a 7 – points Likert scale as follow:
(1)= Strongly disagree ; (2) = Disagree ; (3) = Somewhat disagree ; (4) = Neutral ; (5) = Somewhat agree ; (6) = Agree ; (7) = Strongly agree

Bahagian ini meminta pendapat anda mengenai teknologi pertanian pintar. Sila bulatkan sejauh mana anda bersetuju atau tidak bersetuju dengan setiap pernyataan di bawah menggunakan skala Likert 7-mata seperti berikut:

(1)= Sangat tidak setuju ; (2)= Tidak setuju ; (3) = Agak tidak setuju ; (4) = Neutral ; (5) = Agak setuju ; (6) = Setuju ; (7) = Sangat setuju

No.	Food Security <i>Keterjaminan Makanan</i>							
1.	I believe smart farming technologies adoption may help to increase the crop yield. <i>Saya percaya bahawa penggunaan teknologi pertanian pintar dapat membantu meningkatkan hasil tanaman.</i>	1	2	3	4	5	6	7
2.	I believe smart farming technologies adoption may help to increase my farm's income. <i>Saya percaya penggunaan teknologi pertanian pintar dapat membantu meningkatkan pendapatan ladang saya.</i>	1	2	3	4	5	6	7
3.	I believe smart farming technologies adoption may help to improve capacity utilisation. <i>Saya percaya bahawa penggunaan teknologi pertanian pintar dapat membantu meningkatkan penggunaan kapasiti ladang.</i>	1	2	3	4	5	6	7
4.	I believe smart farming technologies adoption may help improve the efficiency of the farm. <i>Saya percaya penggunaan teknologi pintar dapat membantu meningkatkan kecekapan ladang.</i>	1	2	3	4	5	6	7
5.	I believe smart farming technologies adoption may help to increase the farm's profitability. <i>Saya percaya bahawa penggunaan teknologi pertanian pintar dapat membantu meningkatkan keuntungan ladang.</i>	1	2	3	4	5	6	7

“END OF SURVEY QUESTIONNAIRE. THANK YOU FOR YOUR CONTRIBUTION”

“SOAL SELIDIK TAMAT. TERIMA KASIH ATAS SUMBANGAN ANDA”

APPENDICES 2: SPSS OUTPUT

Table 2A
Outliers

	Statistic	
PE1	Mean	6.18
	5% Trimmed Mean	6.21
PE2	Mean	6.15
	5% Trimmed Mean	6.18
PE3	Mean	6.12
	5% Trimmed Mean	6.14
PE4	Mean	6.11
	5% Trimmed Mean	6.14
PE5	Mean	6.08
	5% Trimmed Mean	6.12
EE1	Mean	5.95
	5% Trimmed Mean	6.02
EE2	Mean	6.05
	5% Trimmed Mean	6.09
EE3	Mean	5.95
	5% Trimmed Mean	6.00
EE4	Mean	6.11
	5% Trimmed Mean	6.15
EE5	Mean	6.05
	5% Trimmed Mean	6.10
SI1	Mean	6.01
	5% Trimmed Mean	6.06
SI2	Mean	5.99
	5% Trimmed Mean	6.02
SI3	Mean	5.99
	5% Trimmed Mean	6.05
SI4	Mean	5.92
	5% Trimmed Mean	5.94
SI5	Mean	5.93
	5% Trimmed Mean	6.01
FC1	Mean	5.92
	5% Trimmed Mean	5.98
FC2	Mean	5.80
	5% Trimmed Mean	5.83

FC3	Mean	5.87
	5% Trimmed Mean	5.91
FC4	Mean	5.82
	5% Trimmed Mean	5.85
FC5	Mean	6.14
	5% Trimmed Mean	6.21
AW1	Mean	5.95
	5% Trimmed Mean	6.07
AW2	Mean	5.99
	5% Trimmed Mean	6.07
AW3	Mean	5.88
	5% Trimmed Mean	5.99
AW4	Mean	5.88
	5% Trimmed Mean	5.92
AW5	Mean	6.11
	5% Trimmed Mean	6.14
AC1	Mean	6.17
	5% Trimmed Mean	6.20
AC2	Mean	6.10
	5% Trimmed Mean	6.12
AC3	Mean	6.09
	5% Trimmed Mean	6.11
AC4	Mean	6.15
	5% Trimmed Mean	6.16
AC5	Mean	6.11
	5% Trimmed Mean	6.14
FS1	Mean	6.14
	5% Trimmed Mean	6.15
FS2	Mean	6.07
	5% Trimmed Mean	6.10
FS3	Mean	6.01
	5% Trimmed Mean	6.04
FS4	Mean	6.07
	5% Trimmed Mean	6.11
FS5	Mean	6.13
	5% Trimmed Mean	6.16

Table 2B
Respondents' Demographic Information

Age					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 20 years old	9	2.7	2.7	2.7
	20-29 years old	26	7.9	7.9	10.6
	30-39 years old	74	22.4	22.4	33.0
	40-49 years old	69	20.9	20.9	53.9
	50-59 years old	94	28.5	28.5	82.4
	60 years and above	58	17.6	17.6	100.0
	Total	330	100.0	100.0	

Gender					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	178	53.9	53.9	53.9
	Female	152	46.1	46.1	100.0
	Total	330	100.0	100.0	

Marital Status					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Single	68	20.6	20.6	20.6
	Married	253	76.7	76.7	97.3
	Others	9	2.7	2.7	100.0
	Total	330	100.0	100.0	

Ethnicity					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Malay	147	44.5	44.5	44.5
	Dayak	123	37.3	37.3	81.8
	Chinese	40	12.1	12.1	93.9
	Others	20	6.1	6.1	100.0
	Total	330	100.0	100.0	

Level of Education					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No formal education	45	13.6	13.6	13.6
	Primary school	57	17.3	17.3	30.9
	Secondary school	128	38.8	38.8	69.7
	Certificates	47	14.2	14.2	83.9
	Diploma	23	7.0	7.0	90.9

	University degree and above	30	9.1	9.1	100.0
	Total	330	100.0	100.0	

Years of Farming					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1- 10 years	240	72.7	72.7	72.7
	11 - 20 years	41	12.4	12.4	85.2
	21 years - 30 years	18	5.5	5.5	90.6
	31 years - 40 years	9	2.7	2.7	93.3
	41 years and above	22	6.7	6.7	100.0
	Total	330	100.0	100.0	

Monthly Income					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than RM1500	205	62.1	62.1	62.1
	RM1500 - RM3500	79	23.9	23.9	86.1
	RM3500 - RM5500	26	7.9	7.9	93.9
	RM5500 -RM8500	13	3.9	3.9	97.9
	More than RM8500	7	2.1	2.1	100.0
	Total	330	100.0	100.0	

Table 2C
Descriptive Analysis

Descriptive Statistics									
	N	Min	Max	Mean	Std.	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Deviation	Statistic	Std. Error	Statistic	Std. Error
	c	c	c	c	Statistic	c		c	Error
PE1	330	3	7	6.18	.861	-.519	.134	-.882	.268
PE2	330	3	7	6.15	.820	-.475	.134	-.658	.268
PE3	330	4	7	6.12	.860	-.323	.134	-1.356	.268
PE4	330	4	7	6.11	.840	-.394	.134	-1.007	.268
PE5	330	2	7	6.08	.885	-.617	.134	.225	.268
EE1	330	3	7	5.95	.969	-.567	.134	-.179	.268
EE2	330	4	7	6.05	.848	-.418	.134	-.740	.268
EE3	330	3	7	5.95	.955	-.486	.134	-.336	.268
EE4	330	3	7	6.11	.827	-.504	.134	-.471	.268
EE5	330	3	7	6.05	.908	-.623	.134	-.070	.268
SI1	330	3	7	6.01	.904	-.539	.134	-.260	.268
SI2	330	4	7	5.99	.823	-.246	.134	-.889	.268
SI3	330	3	7	5.99	.919	-.484	.134	-.535	.268
SI4	330	4	7	5.92	.843	-.125	.134	-1.022	.268
SI5	330	3	7	5.93	.998	-.636	.134	-.033	.268
FC1	330	3	7	5.92	.934	-.468	.134	-.303	.268
FC2	330	3	7	5.80	.931	-.198	.134	-.834	.268
FC3	330	4	7	5.87	.888	-.213	.134	-.891	.268
FC4	330	3	7	5.82	.912	-.254	.134	-.712	.268
FC5	330	3	7	6.14	.950	-.768	.134	-.324	.268
AW1	330	2	7	5.95	1.111	-1.180	.134	1.465	.268
AW2	330	2	7	5.99	.977	-.940	.134	1.051	.268
AW3	330	2	7	5.88	1.128	-1.199	.134	1.846	.268
AW4	330	4	7	5.88	.883	-.140	.134	-1.027	.268
AW5	330	3	7	6.11	.872	-.463	.134	-.821	.268
AC1	330	4	7	6.17	.812	-.395	.134	-1.183	.268
AC2	330	4	7	6.10	.819	-.259	.134	-1.283	.268
AC3	330	4	7	6.09	.818	-.242	.134	-1.287	.268
AC4	330	3	7	6.14	.813	-.431	.134	-.729	.268
AC5	330	2	7	6.10	.883	-.656	.134	.295	.268
FS1	330	4	7	6.14	.823	-.291	.134	-1.375	.268
FS2	330	3	7	6.07	.849	-.433	.134	-.505	.268
FS3	330	3	7	6.01	.879	-.321	.134	-.756	.268

FS4	330	2	7	6.07	.880	-.697	.134	.523	.268
FS5	330	4	7	6.13	.847	-.348	.134	-1.287	.268
Valid N (listwise)	330								

Table 2D
Common Method Variance using Harman's Single Factor

Total Variance Explained						
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.842	33.834	33.834	11.842	33.834	33.834
2	2.058	5.881	39.716			
3	1.567	4.478	44.194			
4	1.496	4.274	48.468			
5	1.431	4.088	52.555			
6	1.244	3.555	56.111			
7	1.126	3.218	59.328			
8	1.035	2.957	62.285			
9	1.001	2.861	65.146			
10	.865	2.473	67.619			
11	.792	2.263	69.882			
12	.748	2.138	72.020			
13	.711	2.031	74.051			
14	.659	1.884	75.934			
15	.637	1.819	77.753			
16	.621	1.775	79.529			
17	.593	1.695	81.224			
18	.579	1.654	82.878			
19	.549	1.568	84.446			
20	.510	1.457	85.904			
21	.479	1.368	87.272			
22	.457	1.306	88.578			
23	.433	1.238	89.816			
24	.407	1.161	90.977			
25	.364	1.040	92.018			
26	.354	1.012	93.030			
27	.333	.950	93.980			
28	.324	.927	94.907			
29	.317	.905	95.812			
30	.292	.835	96.647			
31	.269	.768	97.415			
32	.256	.731	98.147			
33	.242	.691	98.837			
34	.226	.645	99.482			
35	.181	.518	100.000			
Extraction Method: Principal Component Analysis.						

APPENDICES 3: SMART-PLS OUTPUT

Table 3A
Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AC	0.767	0.776	0.843	0.518
AW	0.793	0.806	0.855	0.542
EE	0.855	0.857	0.896	0.632
FC	0.797	0.8	0.86	0.552
FS	0.788	0.797	0.854	0.539
PE	0.815	0.829	0.871	0.577
SI	0.805	0.812	0.865	0.564

Table 3B
Outer Loading

	AC	AW	EE	FC	FS	PE	SI	AW x SI	AW x PE	AW x FC	AW x EE
AC1	0.678										
AC2	0.683										
AC3	0.695										
AC4	0.776										
AC5	0.761										
AW1		0.712									
AW2		0.786									
AW3		0.691									
AW4		0.759									
AW5		0.73									
EE1			0.813								
EE2			0.78								
EE3			0.795								
EE4			0.79								
EE5			0.795								
FC1				0.752							
FC2				0.788							
FC3				0.718							
FC4				0.688							
FC5				0.765							
FS1					0.763						
FS2					0.75						
FS3					0.732						
FS4					0.766						
FS5					0.654						

PE1						0.749					
PE2						0.811					
PE3						0.812					
PE4						0.786					
PE5						0.625					
SI1							0.84				
SI2							0.811				
SI3							0.691				
SI4							0.719				
SI5							0.683				
AW x FC										1	
AW x SI								1			
AW x EE											1
AW x PE									1		

Table 3C
Loadings and Cross Loadings

	AC	AW	EE	FC	FS	PE	SI	AW x SI	AW x PE	AW x FC	AW x EE
AC1	0.678	0.368	0.305	0.321	0.357	0.332	0.317	-0.061	-0.108	-0.049	-0.005
AC2	0.683	0.353	0.38	0.262	0.345	0.372	0.359	-0.073	-0.014	-0.036	0.028
AC3	0.695	0.33	0.25	0.292	0.4	0.328	0.343	-0.042	-0.031	-0.014	0.021
AC4	0.776	0.354	0.365	0.407	0.489	0.474	0.439	-0.007	-0.029	0.063	0.081
AC5	0.761	0.377	0.349	0.366	0.441	0.399	0.347	-0.046	-0.034	0.007	-0.014
AW1	0.3	0.712	0.498	0.42	0.364	0.339	0.36	-0.022	-0.062	-0.041	-0.047
AW2	0.343	0.786	0.477	0.485	0.336	0.399	0.378	-0.025	-0.027	-0.052	-0.059
AW3	0.27	0.691	0.532	0.401	0.316	0.352	0.344	0.017	-0.008	-0.007	-0.138
AW4	0.375	0.759	0.451	0.468	0.352	0.372	0.376	-0.027	0.028	-0.025	0.025
AW5	0.467	0.73	0.379	0.421	0.312	0.389	0.456	-0.088	-0.057	-0.048	-0.104
EE1	0.372	0.453	0.813	0.485	0.41	0.511	0.457	0.041	0.043	-0.073	-0.042
EE2	0.383	0.526	0.78	0.484	0.458	0.492	0.446	-0.022	-0.031	-0.053	-0.08
EE3	0.304	0.508	0.795	0.41	0.351	0.456	0.418	0.061	0.051	-0.026	-0.047
EE4	0.398	0.499	0.79	0.469	0.354	0.516	0.483	-0.036	-0.006	-0.083	-0.096
EE5	0.353	0.477	0.795	0.464	0.359	0.452	0.473	-0.039	-0.043	-0.102	-0.081
FC1	0.324	0.434	0.48	0.752	0.333	0.417	0.443	-0.031	-0.013	-0.008	-0.05
FC2	0.374	0.501	0.445	0.788	0.379	0.441	0.477	-0.069	0.034	0.017	-0.054
FC3	0.335	0.42	0.448	0.718	0.386	0.388	0.423	-0.008	0.004	0.012	-0.067
FC4	0.322	0.358	0.347	0.688	0.375	0.324	0.342	-0.029	0.015	0.101	-0.033
FC5	0.362	0.491	0.449	0.765	0.452	0.424	0.524	-0.076	0.018	-0.063	-0.101
FS1	0.42	0.317	0.312	0.363	0.763	0.414	0.421	-0.016	0.011	0.035	0.003
FS2	0.364	0.281	0.386	0.404	0.75	0.433	0.407	0.027	0.06	0.048	0.005
FS3	0.487	0.377	0.366	0.428	0.732	0.413	0.395	0.014	0.073	0.082	0.045
FS4	0.469	0.393	0.382	0.392	0.766	0.372	0.36	0.013	0.029	0.03	0.004
FS5	0.308	0.266	0.354	0.302	0.654	0.34	0.35	-0.051	-0.057	-0.034	-0.051

PE1	0.37	0.429	0.467	0.477	0.407	0.749	0.444	-0.016	0.011	-0.003	-0.045
PE2	0.436	0.393	0.484	0.44	0.434	0.811	0.455	-0.027	-0.028	-0.013	-0.033
PE3	0.423	0.338	0.48	0.373	0.367	0.812	0.355	0.048	0.045	0.076	0.055
PE4	0.468	0.36	0.459	0.395	0.449	0.786	0.393	0.005	0.07	0.005	0.02
PE5	0.311	0.434	0.45	0.375	0.384	0.625	0.368	0.075	0.032	-0.002	0.002
SI1	0.407	0.424	0.471	0.481	0.378	0.453	0.84	-0.049	-0.038	-0.144	-0.049
SI2	0.401	0.422	0.48	0.502	0.471	0.428	0.811	-0.036	0.007	-0.091	-0.028
SI3	0.3	0.297	0.351	0.442	0.35	0.358	0.691	0.051	-0.007	0.033	0.002
SI4	0.394	0.455	0.475	0.471	0.363	0.37	0.719	0.047	0.1	-0.004	0.031
SI5	0.378	0.364	0.363	0.345	0.406	0.366	0.683	0.07	0.002	-0.008	0.04
AW x FC	-0.002	-0.049	- 0.086	0.014	0.05	0.018	-0.063	0.625	0.551	1	0.669
AW x SI	-0.06	-0.048	- 0.002	-0.059	0	0.018	0.018	1	0.556	0.625	0.597
AW x EE	0.034	-0.086	- 0.089	-0.083	0.007	0.002	-0.002	0.597	0.663	0.669	1
AW x PE	-0.058	-0.036	0.002	0.016	0.038	0.035	0.018	0.556	1	0.551	0.663

Table 3D**Heterotrait-Monotrait Ratio of Correlation (HTMT)**

	AC	AW	EE	FC	FS	PE	SI	AW x SI	AW x PE	AW x FC	AW x EE
AC											
AW	0.611										
EE	0.561	0.768									
FC	0.585	0.744	0.705								
FS	0.71	0.564	0.593	0.647							
PE	0.664	0.637	0.736	0.673	0.671						
SI	0.635	0.642	0.686	0.744	0.66	0.655					
AW x SI	0.072	0.055	0.054	0.065	0.037	0.05	0.075				
AW x PE	0.069	0.055	0.047	0.025	0.07	0.054	0.046	0.556			
AW x FC	0.054	0.053	0.091	0.061	0.07	0.029	0.083	0.625	0.551		
AW x EE	0.047	0.114	0.094	0.092	0.033	0.045	0.045	0.597	0.663	0.669	

Table 3E**Model Fit**

	Saturated model	Estimated model
SRMR	0.064	0.085
d ULS	2.601	4.546
d G	0.839	0.881
Chi-square	1579.938	1631.932
NFI	0.719	0.71

Table 3F
Collinearity Test

	VIF
AC1	1.459
AC2	1.402
AC3	1.459
AC4	1.614
AC5	1.58
AW1	1.981
AW2	2.197
AW3	1.463
AW4	1.537
AW5	1.357
EE1	2.089
EE2	1.81
EE3	1.982
EE4	1.715
EE5	2.048
FC1	1.635
FC2	1.689
FC3	1.43
FC4	1.368
FC5	1.568
FS1	1.591
FS2	1.647
FS3	1.366
FS4	1.54
FS5	1.449
PE1	1.758
PE2	1.934
PE3	2.036
PE4	1.829
PE5	1.329
SI1	2.064
SI2	1.964
SI3	1.546
SI4	1.417
SI5	1.354
AW x FC	1
AW x SI	1
AW x EE	1
AW x PE	1

Table 3G
Path Coefficient (significant 5%) and Confidence Interval Bias

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
AC -> FS	0.57	0.574	0.04	14.349	0
AW -> AC	0.19	0.196	0.073	2.608	0.005
EE -> AC	0.034	0.037	0.07	0.485	0.314
FC -> AC	0.071	0.07	0.076	0.934	0.175
PE -> AC	0.279	0.279	0.06	4.662	0
SI -> AC	0.203	0.201	0.063	3.225	0.001
AW x SI -> AC	-0.104	-0.097	0.069	1.507	0.066
AW x PE -> AC	-0.146	-0.144	0.06	2.451	0.007
AW x FC -> AC	0.036	0.039	0.09	0.403	0.343
AW x EE -> AC	0.196	0.187	0.083	2.374	0.009

	Original sample (O)	Sample mean (M)	Bias	5.00%	95.00%
AC -> FS	0.57	0.574	0.004	0.496	0.628
AW -> AC	0.19	0.196	0.005	0.066	0.305
EE -> AC	0.034	0.037	0.003	-0.081	0.15
FC -> AC	0.071	0.07	-0.001	-0.056	0.197
PE -> AC	0.279	0.279	-0.001	0.176	0.373
SI -> AC	0.203	0.201	-0.002	0.096	0.304
AW x SI -> AC	-0.104	-0.097	0.007	-0.211	0.01
AW x PE -> AC	-0.146	-0.144	0.001	-0.24	-0.046
AW x FC -> AC	0.036	0.039	0.002	-0.113	0.183
AW x EE -> AC	0.196	0.187	-0.01	0.065	0.331

Table 3H
Coefficient of Determination (R Square)

	R-square	R-square adjusted
AC	0.417	0.401
FS	0.325	0.323

Table 3I
Effect size (f Square)

	AC	AW	EE	FC	FS	PE	SI	AW x SI	AW x PE	AW x FC	AW x EE
AC					0.481						
AW	0.032										
EE	0.001										
FC	0.004										
FS											
PE	0.073										
SI	0.037										
AW x SI	0.011										
AW x PE	0.023										
AW x FC	0.001										
AW x EE	0.03										

Table 3J
Predictive Relevance (Q Square)

	SSO	SSE	Q ² (=1- SSE/SSO)
AC	1650	1308.265	0.207
AW	1650	1650	0
EE	1650	1650	0
FC	1650	1650	0
FS	1650	1376.367	0.166
PE	1650	1650	0
SI	1650	1650	0

APPENDICES 4: COLLECTION DATA



APPENDICES 5: MODERATOR ANALYSIS

The term moderating variable denotes a factor that impacts the direction and magnitude of an antecedent that affects an outcome (Aguinis et al., 2017). Moderation is defined statistically as the degree to which the value of a moderator variable influences the relationship between an independent and dependent variable (Dawson, 2014). Furthermore, moderating variables are crucial in determining whether the relationship between two variables is consistent across groups. Generally, a moderating model examines the circumstances or individuals for whom a particular variable significantly accounts for or influences a dependent variable (Frazier et al., 2004).

The conceptual model illustrated in Figure 4.2 is an example of moderation analysis. A moderator (M), an independent variable (X), and a dependent variable (Y) comprise them. An arrow connecting the moderating variable to the dependent and independent variables indicates the correlation between X and Y. Nevertheless, the statistical representation diverges from the graphical representation in the model due to the inclusion of an interaction term denoted as $X*M$ (Z).

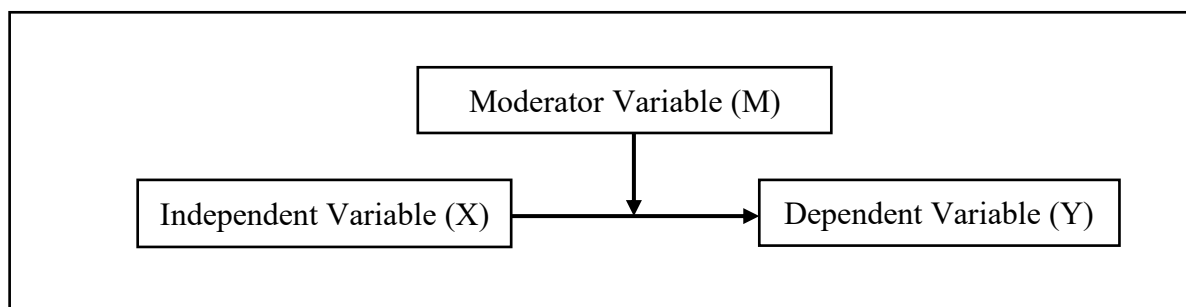


Figure 1: Example of the Conceptual Framework

As illustrated in Figure 4.3, the statistical model for moderation incorporates an interaction term (Z) that pertains to the dependent variable. Memon et al. (2019) mentioned

that the term moderator can be interpreted in various ways. When nominal or ordinal scales are employed, the variable is a categorical one such as male and female; public universities and private universities; when interval scales are utilised, the variable is a continuous one such as high level and low level of scepticism; high level and low level of organisational support.

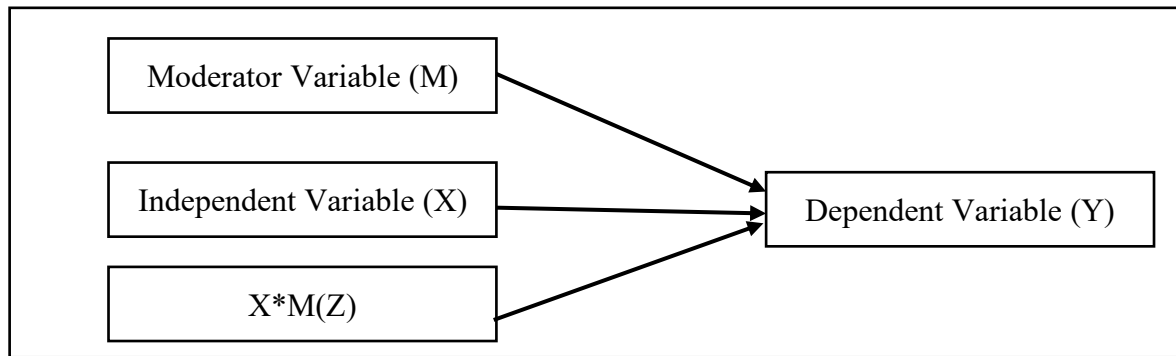


Figure 2: Statistic Model

Andersson et al. (2014) proposed a seven-step process to conceptualise or hypothesise moderating relationships. The proposed framework mandates the following from researchers: (1) Determine the theoretical framework that elucidates the direct and moderating effects; (2) Employ the selected theory to address the research inquiry and explain the mechanisms underlying the direct effect; (3) Offer a theoretical rationale for the selection of the moderator variable (M); and (4) Elucidate the direct impact of the moderator variable (M) on the dependent variable (Y) to distinguish it from the moderating effect. (6) Discontinue the possibility of a reverse interaction where the independent variable (X) moderates the relationship between the moderating variable (M) and the dependent variable (Y) in a theoretical sense. (7) Interpret the results in light of theory and explain from a theoretical perspective. Adaptation and modification of these stages are possible based on the particular research inquiry and the characteristics of the investigation.

Furthermore, Aguinis et al. (2017) explicitly stated the directionality of the interaction by hypothesising, based on the literature, that the relationship can be either positive or negative. For instance, "The presence of M will increase the impact of X on Y" or "A reduction in M will strengthen the relationship between X and Y." Gardner, Harris, Li, Kirkman, and Mathieu (2017) proposed that moderators may exert three distinct categories of interaction effects. Moderators can (1) enhance the intensity of a relationship, (2) diminish its intensity, or (3) invert or alter the nature of the relationship.

APPENDICES 6: COLLINEARITY TEST

In assessing common method bias, the collinearity test is an additional statistical examiner. An examination of both vertical and lateral collinearity is conducted concurrently using this systematic approach (Kock & Lynn, 2012). This examination was conducted using Smart-PLS. Collinearity, or inter-correlation, is a statistical condition characterised by a strong correlation among the independent variables. This limitation is unique to multiple regression models; basic regressions do not possess it.

As a result, the linear relationships between all independent and dependent variables cannot be determined due to the distortion of the t-test coefficients. Beyond that, multicollinearity does not affect the f test of the analysis of variance; however, it does confound the interpretation of the coefficients. Potentially undermining the statistical significance of particular predictor variables, multicollinearity can increase the variances of the estimated parameters, even if the model as a whole is significant (Midi et al., 2010). Multicollinearity can, therefore, lead to significant complications in both the estimation and interpretation of beta. Multicollinearity can be detected by examining the correlation matrix, VIF, and eigenvalues. The VIF measures the incidence of multicollinearity in an ordinary least squares regression analysis. The index quantifies the degree to which the estimated coefficients' variance is augmented compared to the scenario where the X variables do not correlate. According to Montgomery (2001), a rule of thumb dictates that the associated regression coefficients are inadequately estimated due to multicollinearity if either of the VIF values surpasses 5 or 10. A VIF value below 3.3 was suggested as the optimal threshold for this test; any higher than that value would suggest the presence of pathological collinearity, which could indicate common method bias contaminating the model (Kock, 2015).