Examining the key influences on farmers' intentions to adopt Smart Farming Technology

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Declaration

The author hereby declares that, except where duly noted and referenced, this research study and resulting thesis is entirely her own work and has not been submitted for any degree or other qualification in South East Technological University or any other third level institution in Ireland or internationally.

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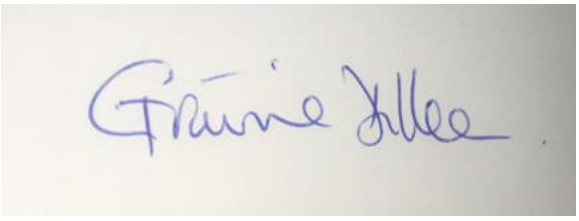

Gráinne Dilleen

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Acknowledgements

I never thought that the day would come to submit this PhD; it has been a labour of love and a huge learning curve. As I started the process, people spoke about the journey and, as I reflect now, I most certainly understand that. It definitely has been a journey, at times stressful, but mostly enjoyable.

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Abstract: Examining the key influences on farmers' intentions to adopt Smart Farming Technology – Gráinne Dilleen

Smart Farming Technology (SFT) has been recognised as a potential solution to the many challenges facing the agricultural sector. SFT is information and communication technologies, and smart devices deployed on-farm to help optimise operations. However, the adoption rate of SFT has been slower than expected.

The overarching objective of this study was to identify and examine the factors influencing the farmer's behavioural intention (BI) to adopt SFT. The research sought to develop and empirically test a model to advance substantive theory. The Technology Acceptance Model (TAM) served as the guiding framework. A series of hypotheses were developed, based on the extant literature. A deductive approach was undertaken, using a cross-sectional study to test the validity of the hypotheses. An online survey was used for data collection, yielding two hundred and seventeen valid responses from farmers. Confirmatory factor analysis and structural equation modelling were used to test the hypothesised relationships between variables.

Overall, the findings confirm that the farmer's BI to adopt SFT is directly influenced by the perceived usefulness (PU) of the technology and the personal innovativeness (PIIT) of the farmer. PU had the strongest relationship with BI, thus demonstrating the importance of highlighting the increased efficiency and productivity delivered by SFT. PIIT also directly influenced the PU and perceived ease of use of SFT, indicating the need to develop innovativeness as a personality trait in farmers. Social influence directly affected PU, determining the importance of the farmer's network in shaping perceptions of SFT. Finally, PU had a positive, direct influence on trust in the SFT vendor.

The major theoretical contribution is the development of a novel, integrated model which empirically verifies the key influences on the farmer's BI to adopt SFT. Furthermore, the research advances TAM by including additional antecedent variables to increase its explanatory and predictive power.

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List of Abbreviations

AI	Artificial Intelligence
AIC	Akaike's Information Criterion
AMOS	Analysis of Moment Structures
AVE	Average Variance Extracted
B2B	Business-to-Business
B2C	Business-to-Consumer
BI	Behavioural Intention
CAP	Common Agricultural Policy
CB-SEM	Covariance-based SEM
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CMB	Common Method Bias
CR	Construct Reliability
CV	Convergent Validity
DMU	Decision-Making Unit
DoI	Diffusion of Innovations Theory
DV	Discriminant Validity
ECVI	Expected Cross Validation Index
EU	European Union
FMIS	Farm Management Information Systems
GLS	Generalised Least Squares
GPS	Global Positioning Systems
HTMT	Heterotrait-Monotrait Ratio of Correlations
ICT	Information Communication Technology
IFA	Irish Farmers' Association
IFI	Incremental Index of Fit
IoT	Internet of Things
IS	Information Systems
IT	Information Technology
KMO	Kaiser-Meyer-Olkin
MI	Modification Indices
ML	Maximum Likelihood
OBB	Organisational Buying Behaviour
PA	Precision Agriculture
PAT	Precision Agriculture Technologies
PBC	Perceived Behavioural Control
PEOU	Perceived Ease of Use
PIIT	Personal Innovativeness in IT domain
PLS-SEM	Partial Least Squares - SEM
PNB	Perceived Net Benefit
PNFI	Parsimony Normed-Fit Index
PU	Perceived Usefulness
Q-Q	Quantile-Quantile
RMSEA	Root Mean Square Error of Approximation
SCT	Social Cognitive Theory
SEM	Structural Equation Modelling
SET	Social Exchange Theory
SETU	South East Technological University

SFT	Smart Farming Technology
SI	Social Influence
SIC	Squared Inter-Construct Correlation
SME	Small and Medium Enterprise
SN	Subjective Norm
SPSS	Statistical Package for the Social Sciences
SRMR	Standardized Root Mean Square Residual
TA	Technology Acceptance
TAM	Technology Acceptance Model
TLI	Tucker Lewis Index
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TRI	Technology Readiness Index
UAV	Unmanned Aerial Vehicles
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor

Publications relating to this research

Doolin, K., Roussaki, I., Dilleen, G., Cleary, E., Williams, H., Foley, A. and Claffey, E. “Making Smart Agriculture Smarter: Challenges in Realizing an IoT-Enabled Agricultural Ecosystem”, in *Springer Handbook of IoT* (forthcoming, January 2024)

Dilleen, G., Claffey, E., Foley, A. and Doolin, K. (2023), "Investigating knowledge dissemination and social media use in the farming network to build trust in smart farming technology adoption", *Journal of Business & Industrial Marketing*, Vol. 38 No. 8, pp. 1754-1765

Hearne, D., Wolferts, D. and Dilleen, G. (2022), “Designing technology for farmers: A case study in the application of Human-Centered Design for the DEMETER project” *Proceedings of the First International Conference on Farmer-centric On-Farm Experimentation*, Montpellier, 12-15 October, pp. 143-152

Dilleen, G., Claffey, E. and Foley, A. (2022), “Exploring the role of trust as an antecedent to the adoption of Smart Farming Technology”, *IAM Annual Conference,* Dublin, 24-25th August

Dilleen, G., Claffey, E. and Foley, A. (2021), “Investigating the External and Internal influences on Farmers’ Adoption of Smart Farming Technologies”, *IMP Conference,* Virtual, 26-27th August

Dilleen, G., Claffey, E. and Foley, A. (2021), “Examining the Internal and External Forces which Impact Adoption of AgriTech in the Marketplace”, *IAM Annual Conference* (Doctoral Colloquium), Virtual, 25-26th August

Dilleen, G., Claffey, E. and Foley, A. (2021), “Determining the farmer’s decision-making process when adopting smart farming technologies”, *WIT Postgraduate Conference,* Virtual, 22nd January

Dilleen, G., Claffey, E. and Foley, A. (2020), “Determining the farmer’s decision-making process in adopting smart farming technologies - a business marketing perspective”, *IAM Annual Conference* (Doctoral Colloquium), Virtual, 26th August

Chapter 1: Introduction

1.1 Research Background

The overarching research objective of this study is to examine the key influences on farmers' intentions to adopt Smart Farming Technology (SFT). Agriculture is facing many challenges which are well documented, including increased environmental concerns, heightened by intensified agricultural production to feed a growing population (Balafoutis *et al.*, 2020; Campbell *et al.*, 2014; Muhie, 2022). For example, agricultural irrigation accounts for approximately 70 per cent of the world's water consumption (Charania and Li, 2020), while between 10-30 per cent of greenhouse gas emissions are related to agriculture (Laborde *et al.*, 2021; Le Quéré *et al.*, 2016; Smith *et al.*, 2014). These environmental factors are negatively impacting the biodiversity of the land (Agovino *et al.*, 2019; Egal and Berry, 2020), and are a major threat for agriculture. According to the United Nations (2017), it is estimated that the world population will grow to 8.6 billion in 2030 and to 9.8 billion in 2050. To sustain this population growth, food production will have to increase by an estimated 70 per cent by 2050 (FAO, 2009; Hunter *et al.*, 2017). Intensified production and climate change concerns will undoubtedly further increase the strain on natural resources, which could result in drought (Christian *et al.*, 2023; Gondchawar and Kawitkar, 2016) and a reduction in certain crop yields by as much as 50 per cent by 2080 (Challinor *et al.*, 2014; Hristov *et al.*, 2020). This is driving the need for more sustainable agricultural methods (Basso and Antle, 2020; Javaid *et al.*, 2022; Long *et al.*, 2016; Musa and Basir, 2021). Furthermore, labour shortages, income inequity, increased urbanisation and an ageing farm population all pose real challenges for the agricultural sector (Bren d'Amour *et al.*, 2017; European Parliament, 2016; O'Meara, 2019; Rotz *et al.*, 2019b; Ryan, 2023).

Consequently, SFT has been identified as a potential solution to many of these challenges (Kernecker *et al.*, 2019; Moysiadis *et al.*, 2021). However, the adoption rate of SFT is quite low and fragmented (Adnan *et al.*, 2019; Ingram *et al.*, 2022; Vecchio *et al.*, 2020). Overall adoption figures are difficult to ascertain due to the complexity of the farming sector owing to heterogeneity in farm size, structure and type (Hubbard, 2009). Further discussion on the adoption rate is presented in Section 1.2. Nevertheless, it is evident that learning and understanding the factors which influence farmers to adopt SFT is important for several actors in the agriculture sector, including policymakers, technology providers, educators and indeed farmers (Balafoutis *et al.*, 2020; Giua *et al.*, 2022; Kim and

Cameron, 2013; Thompson *et al.*, 2018). Identifying this gap in knowledge led to the main goal of this doctoral study: to examine the key influences on farmers' intentions to adopt SFT. A comprehensive understanding of these determinants is important in facilitating and enhancing a greater intention to adopt SFT. This study, therefore, identifies the factors influencing the farmer's behavioural intention to adopt SFT. A model is developed and presented, empirically testing the relationships between several factors which include the farmer's perceptions of the technology, the personal innovativeness of the farmer, trust in the SFT vendor, social influence, and the impact of these factors on the behavioural intention to adopt SFT. This model aims to delineate how these factors collectively inform and shape the behavioural intention of farmers to adopt SFT.

The following section, 1.2, briefly gives an overview of SFT, and its potential impact on the agriculture sector. This section also includes a discussion on the adoption rate of SFT across the farming sector. Section 1.3. introduces DEMETER, the Horizon 2020 project funding this research. In Section 1.4, the gaps in knowledge through an extensive literature review are presented, justifying the importance of this study. The overall research aim and objective is presented in Section 1.5, which also presents the research context and the research domains. Finally, Section 1.6 concludes with a summary of the thesis outline.

1.2 Smart Farming Technology (SFT)

SFT encompasses a broad range of technologies that can be used on-farm to help and improve cultivation, yield output, work-life balance, and decision-making (Knierim *et al.*, 2018). There is, however, no consensus related to an actual definition of what constitutes SFT (Osrof *et al.*, 2023). For example, terms such as precision agriculture, digital farming and agriculture 4.0 have often been used interchangeably when discussing SFT (Klerkx *et al.*, 2019). Nonetheless, as discussed in greater detail in Section 2.2, the categories of SFT used for this study are based on the research of Balafoutis *et al.* (2020, p. 2) and Kernecker *et al.* (2021) who broadly classify SFT into three categories: 1) farm management information systems (FMIS) that manage data to support farm operations, 2) precision agriculture (PA) systems and GNSS (global navigation satellite systems), and 3) automated systems such as robotics and artificial intelligence.

As discussed very briefly in Section 1.1, the adoption rate of SFT is detailed as being low, although determining actual figures is difficult. For example, Osrof *et al.* (2023) highlight that the adoption rate of SFT is undocumented in many developing countries. Similarly, Vecchio *et al.* (2020) explain that although government bodies have been promoting the benefits of precision farming technology for several years, the adoption rate still remains low. However, no further clarification related to the exact adoption figures is outlined. Many of the adoption figures which are cited in the extant literature relate to the use of precision agriculture technology (PAT), which Karunathilake *et al.* (2023) describe as cutting edge technologies using data to improve productivity on-farm and improve sustainability. However, precision agriculture systems are detailed as one category of SFT, as outlined by Balafoutis *et al.* (2020), and thus are useful to examine.

The difficultly in measuring SFT or PAT adoption is due to the lack of a unified approach to measurement, as outlined by Pavlenko *et al.* (2023). Furthermore, adoption differs according to country, farming context and farm type (da Silveira *et al.*, 2023; Kernecker *et al.*, 2019). For instance, OECD (2016) report that the use of PAT is most advanced among large-scale arable farmers, particularly in developed countries of Europe, and the US and Australia. However, Lowenberg-DeBoer and Erickson (2019) determine that Europe still lags behind the US and Australia in terms of adoption. Data from the European Parliament (2016) estimated that only 25% of EU farms were using technology that consisted of a precision agriculture element, with the adoption rate being higher among north-western European countries. Similarly, CEMA (2016) determined that the use of precision farming technologies among EU farmers was low, stating that, for example, only 35% of fertiliser spreaders sold used a precision technology element. This figure was even lower in Ireland at only 6%. While these adoption figures are somewhat dated, they remain relevant as it highlights the ongoing challenges in the uptake of SFT and PAT.

In the absence of unified official figures, most of the data is gathered from academic surveys or project-based surveys (OECD, 2016). Lawson *et al.* (2011) examined the adoption of robotic milkers, automated feeding systems, automated grain labelling and grain-drying and auto-guidance systems across German, Greek, Finnish and Danish farmers. They found that the adoption rate varied between 0%-50%, depending on the technology, with the most popular being automated feeders among Danish farmers at 50%. Auto-guidance technology adoption in general was low between 2-12%. Similarly, in a study from Soto *et al.* (2019) determining awareness and adoption of PAT among wheat and potato farmers in the Netherlands, UK, Belgium, Germany and Greece, they deduce that awareness of PAT is high. In particular, the awareness of machine guidance and variable rate application technologies was high at 94% and 79% respectively. However, on average, adoption of these technologies was lower at 34% and 22%. Kernecker *et al.* (2019) conducted a study of 287 farmers' SFT adoption across seven EU countries (Greece, Germany, France, Netherlands, Serbia, Spain and the UK). In particular, they focused on recording and mapping technologies, GPS-based steering tools, FMIS, and autonomous machines. They found a 50% adoption rate of SFT in total, but determined a significant difference based on country, farm size and farm type. For example, farmers from Greece and Serbia had much lower rates of adoption than Germany, the Netherlands, and the UK. Arable farmers were most likely to adopt SFT due to the farm size, compared to vineyard farmers. However, exact figures were not presented. Similarly, Barnes *et al.* (2019b) conducted an analysis of the adoption of PAT among 971 arable farmers across Germany, the UK, Netherlands, Belgium and Greece. They assessed the use of machine guidance and variable rate technology and found an adoption rate ranging from 23.5% in Belgium to 77% in the UK. However, again they found significant differences based on location, farm size and farm income. In their study, Vik *et al.* (2022) outline the adoption rate for automatic milking systems to be in the single digit percentage for UK farmers, but rising to 25% in Norway. Gabriel and Gandorfer (2022) assessed small-scale Bavarian farmers use of PAT and other digital technologies and found adoption rates which rarely ventured above 10%. In summary, research from both public bodies and academic studies demonstrates the difficultly in ascertaining the overall adoption rate of SFT and PAT but that overall adoption across the EU is limited. However, it can be concluded that the adoption rate varies considerably based on farm type, farm size, location, farm income and the technology being adopted. Thus, further research investigating the factors influencing the adoption of SFT is necessary (Dibbern *et al.*, 2024; Osrof *et al.*, 2023).

In addition, Higgins and Bryant (2020) determine that SFT is primarily used by farmers to increase agricultural productivity. Adoption changes the farmer's decision-making process on-farm, moving away from experience and focusing on data to drive decisions (Eastwood *et al.*, 2017b). However, it should be noted although SFT adoption brings many positives, it is not without risk in terms of socio-ethical issues particularly related to data privacy and skills development (Reichelt and Nettle, 2023). The literature review, presented in Chapter 2, discusses the advantages and disadvantages associated with SFT adoption in more detail.

1.3 DEMETER

This research is funded by the DEMETER project under Horizon2020, the EU framework programme for research (European Commission, 2019). Several such European projects have been funded to better understand technology adoption in an agricultural context (European Commission, 2019). The project ran from September 2019-September 2023, with the main objective of driving the adoption of interoperable, smart farming solutions. Pilot projects were used to test the viability and capabilities of the technologies and their interoperability mechanisms, across several farming contexts: arable crops, fruits and vegetables and livestock rearing (DEMETER, 2019). The researcher was embedded in the project, working in a marketing capacity, for its duration. As discussed in Chapter 4, Research Design and Methodology, this was considered and reinforced the use of a quantitative survey to minimise the impact of bias. Furthermore, as discussed in the limitations of the research in Section 7.6, the researcher acknowledges that researcher confirmation bias or funding bias could unknowingly have been present.

1.4 Research Justification and Theoretical Rationale

A key strategic, and often difficult, decision for the farm business centres around the deployment of new technologies to improve production processes (Gray *et al.*, 2003). Consequently, farmers' technology adoption decisions have been the subject of considerable research (Aubert *et al.*, 2012; Barnes *et al.*, 2019b; Läpple *et al.*, 2015; Lima *et al.*, 2018; Long *et al.*, 2016; Tamirat *et al.*, 2017). However, as outlined in the literature review in Section 2.2, agriculture is lagging behind other industries in terms of ICT and technology adoption research (Aubert *et al.*, 2012). Pivoto *et al.* (2018) and de Oca Munguia and Llewellyn (2020) deduce that the body of literature on SFT adoption is relatively new and thus lacking consensus. Bukchin and Kerret (2018) support this by explaining how the literature is lacking a comprehensive overview of the factors which influence farmers' intentions to adopt technology. Understanding the farmer's interest in and their adoption of SFT is key to understanding if, and how, SFT can improve agricultural sustainability (Kernecker *et al.*, 2019). Shang *et al.* (2021) assert that while there are several studies addressing adoption of smart technology in agriculture, the volume of these studies is considerably lower than those examining agriculture practices such as sustainable farming. Thus, more studies on SFT adoption are needed (Barnes *et al.*, 2019b; Idoje *et al.*, 2021; Osrof *et al.*, 2023).

Caffaro *et al.* (2020) call for more research widening the range of SFT being investigated. Much of the literature focuses on individual technologies such as drones and sensors, which limits generalisability (Bacco *et al.*, 2018; Khatri-Chhetri *et al.*, 2017; Läpple *et al.*, 2015; Rutten *et al.*, 2018; Sauer and Zilberman, 2012). Therefore, this study concentrates on the three categories of SFT as discussed in Section 1.2 and Section 2.2. In addition, the extant literature is also lacking studies which address the multiple elements of technology adoption (Pathak *et al.*, 2019). Of the research that exists, most focuses on socio-economic factors such as age, education and farm size (Adrian *et al.*, 2005; Carrer *et al.*, 2017; Mahindarathne and Min, 2018; Pierpaoli *et al.*, 2013). Often psychological, organisational and social factors are largely ignored (Buyinza *et al.*, 2020; de Lauwere *et al.*, 2020; Migliore *et al.*, 2014; Ronaghi and Forouharfar, 2020; Unay-Gailhard and Bojnec, 2016). This research directly addresses this gap by including social, psychological and organisational factors such as the farm size.

The Technology Acceptance Model (TAM) from Davis (1986) is used as the guiding theoretical framework for this study. As discussed in Section 2.8, TAM is viewed as a leading theory when examining the adoption and use of new technologies, with considerable empirical support (El-Gohary, 2012; Granić and Marangunić, 2019; King and He, 2006; Sun and Zhang, 2006). However, despite its popularity, it is criticised for being overly parsimonious (Straub and Burton-Jones, 2007) and for failing to examine the antecedents to the TAM variables of perceived usefulness and perceived ease of use (Venkatesh *et al.*, 2007). Moreover, Bagozzi (2007a) highlights the limitations of TAM as failing to identify antecedent determinants and insufficient examination of the impact of social factors. Thus, the distinct need to incorporate additional variables with TAM to improve its explanatory power, contextual relevance and to address the gaps outlined previously.

Examination of the literature reveals that the influence of the farmer's network on technology adoption has not been extensively examined in empirical studies (Shang *et al.*, 2021). Understanding the role of social influence is particularly important in the context of technologies that offer utilitarian benefits (Eckhardt *et al.*, 2010), which it can be argued that SFT does. However, Burton (2004) outlines that many studies which use a behavioural approach to understand technology adoption in agriculture fail to account for social influence. Thus, Jayashankar *et al.* (2018) explicitly call for more research to determine how the farmer's network facilitates technology adoption. This network consists of peer farmers, farm advisors, associations, cooperatives, material providers, vendors, agribusinesses, artifacts and organisational structures (Joffre *et al.*, 2019). Therefore, understanding the dynamics of these networks could provide valuable insights into the social dimensions of technology adoption in the agricultural sector, offering a more integrated view of the factors influencing farmers' intentions to adopt SFT.

Moreover, as highlighted in Section 2.8.5.2, the rate at which individuals adopt or show intention to adopt new technologies can vary significantly, which can be partly attributed to differences in personality (Agarwal and Prasad, 1998; Marcati *et al.*, 2008; Rogers, 2003; Venkatesh, 2021). In the context of agriculture, several researchers determine a gap in understanding how farmer personality traits impact behaviour (Ali *et al.*, 2017; Bukchin and Kerret, 2018; Rose *et al.*, 2018c). This has resulted in a call for more studies which examine the effect of personality on intention to adopt technologies, across new and different contexts (Agyei *et al.*, 2020; Barnett *et al.*, 2017; Ozbek *et al.*, 2014; Svendsen *et al.*, 2013). In particular, innovativeness as a personality trait is determined to be an influential factor in both the perception and adoption of new technologies (Abubakre *et al.*, 2020; Ciftci *et al.*, 2021; Dabholkar and Bagozzi, 2002; Fagan *et al.*, 2012; Goldsmith and Foxall, 2003).

Individual characteristics such as age, gender and education can influence the perceptions and intention to adopt technologies, acting as moderators or control variables (Venkatesh *et al.*, 2003). However, the literature is conflicted concerning how these variables impact the intention to adopt SFT. For example, Zheng *et al.* (2018) find that male farmers in China have a higher intention to adopt drone technology than females. Conversely, Rübcke von Veltheim *et al.* (2021) determine that gender has no influence on farmers' intentions to use autonomous field robots. Giua *et al.* (2022) outline that age is not a statistically significant influence on farmers' intentions to adopt SFT. However, Groher *et al.* (2020) find that older farmers are less likely to adopt digital or smart farming technologies. With regard to education, several researchers determine that farmers who have a lower level of education have a lower intention to adopt technology (Caffaro and Cavallo, 2019; Marescotti *et al.*, 2021; Paxton *et al.*, 2011; Pierpaoli *et al.*, 2013; Pivoto *et al.*, 2019). Thus, a nuanced analysis of the effect of these personal characteristics on the intention to adopt SFT is necessary.

The adoption of SFT has been hampered by farmer scepticism and hesitancy (Newton *et al.*, 2020; Reichardt and Jürgens, 2009). Often this can be attributed to lack of trust in the technology or the technology provider (He *et al.*, 2015; Jakku *et al.*, 2019; van der Burg *et al.*, 2019; Wolfert *et al.*, 2017). For example, Eastwood and Renwick (2020) highlight that farmers often struggle with technology adoption due to poor relationship management and lack of competency from the vendor. However, as outlined in Section 2.5.4 and 2.8.5.3, trust is an important concept in B2B relationships, helping to reduce feelings of doubt, uncertainty and apprehension (Allen and Wilson, 2003; Bhattacherjee, 2002; Kemp *et al.*, 2018). Furthermore, Pavlou (2003) argues that trust in the technology provider or vendor must be present first, if the user is to have trust in the actual technology. This highlights that trust is an important construct to examine in the context of technology adoption. These deficiencies and gaps in the existing body of literature give rise to the overall research aim and objective as outlined below.

1.5 Research Aim and Objective

The overarching objective of this research is to develop and test a model of farmers' behavioural intention to adopt SFT, in an attempt to advance substantive theory on the key determinants of this behaviour. A significant objective of this model is to ensure its broad applicability and generalisability across various contexts. This leads to the following research question:

What are the key factors influencing the farmer's behavioural intention to adopt Smart Farming Technology?

This overall question leads to the development of a series of sub-questions which highlight the key relationships, as outlined by the literature review in Chapter 2, to be addressed:

- *How does the farmer's perceptions and attitudes influence the intention to adopt SFT?*
- *How does personal innovativeness, as a personality trait, influence the farmer's intention to adopt SFT?*
- *To what extent does social influence impact the farmer's intention to adopt SFT?*
- *How does trust in the SFT vendor influence the farmer's intention to adopt SFT?*

To answer the above research questions and to build a conceptual model, it is necessary to determine the research context and draw from literature across several domains, namely Technology Adoption, Industrial Marketing and Agricultural Science.

1.5.1 Research Context

Ajzen (2020) determines that to understand behaviour, it is necessary to clearly define the target market of interest, the precise action involved and the context under which it happens. The target market or unit of analysis for this study is the farmer, across a range of farm sizes and farm types. Dockès *et al.* (2018) highlight that the identity of farmers is constantly changing and takes many forms from small farmers to larger commercial entities. There is no single definition of what constitutes a small or large farm due to differences in physical farm size across Europe. However, within the EU, it is recognised that three types of farms exist; first, semi-subsistence farms where the focus is to feed the farmer and their families; second, small and medium sized farms that mainly function as a family business and third, large agriculture farms which operate as legal entities or as part of a cooperative (Eurostat, 2018). Specifically, the target market of this study is small to very large sized farms. This research recognises that not all farmers are driven by profit, but equally that a consistent income source is critical to the farm's survival. Examining the size of farm is important, as discussed in Section 2.5.2.1, as scale is proven to influence both the profitability of the SFT investment and access to capital (Konrad *et al.*, 2019). Including smaller farms in the study is essential as they are recognised as central to rural sustainability in Europe (Guiomar *et al.*, 2018) but the factors impacting SFT adoption differ to larger farms (Pierpaoli *et al.*, 2013). Furthermore, the use of technology is seen as a substantial support to smaller farms, allowing them to increase productivity (Bukchin and Kerret, 2020). Regan (2019) highlights that SFT can be too expensive for the smallholder farmer, but on the other hand, smaller scale SFT still deliver benefits. Furthermore, it is recognised that some farmers may already have a SFT on farm, thus the research focuses on adopters and non-adopters, as farmers can deploy more than one SFT or category of SFT on farm.

Farming is a broad category including livestock, tillage, fruit and vegetable production, viticulture, aquaculture, forestry, and insect production. Understanding the adoption of SFT across all categories of farming is beyond the scope of this research. McElwee (2004) and Vesala *et al.* (2007) define a farmer as a person working either full-time or part-time on farm-related activities which involve growing crops, managing livestock or soil cultivation with the main purpose of earning an income. Taking this definition, farming in this study relates to livestock rearing, crop cultivation and the plantation of fruits and vegetables.

The precise action in the context of this study is the intention to adopt SFT, as detailed in Section 2.8.1. Due to the time constraint of the research, it is not possible to measure actual adoption and usage of such technologies, as a longitudinal study would be needed. However, understanding intention is important as it is shown to influence adoption and helps to predict actual behaviour (Ajzen, 1991; Taylor and Todd, 1995; Venkatesh *et al.*, 2023). Key behavioural change models such as the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology (UTAUT) from Venkatesh *et al.* (2003) indicate that behavioural intention exerts a positive effect on technology usage.

As outlined in Section 1.2 and 2.2, three categories of SFT exist: 1) farm management information systems (FMIS) 2) Precision Agriculture (PA) and GNSS 3) automated systems such as robotics and artificial intelligence (Balafoutis *et al.*, 2020). FMIS are described as technologies or systems that enable the collection, storage, sharing and interpretation of data relating to farm operations. PA technologies (PAT) improve farm management through monitoring and inter and intra-field variability in crops. Finally, automated and robotic SFT are centred around providing automatic control, artificial intelligence, and robotic platforms to aid in agriculture production and decision making (ibid). As the nature of farming and the types of SFT available are diverse, this research is not limited to a particular category of SFT or indeed individual technology. Consequently, the three broad categories of SFT are thus addressed, supporting Läpple *et al.* (2015) and Sauer and Zilberman (2012) who call for more research on the category of SFT, rather than focusing on a particular technology.

1.5.2 Research Domains

The context of this study is the intention to adopt SFT, thus an in-depth review of the Technology Adoption and Information Systems literature is presented in Sections 2.7 and 2.8. In addition, Austin *et al.* (1998) determine that delving into the fields of psychology, sociology and economics is necessary to better understand farmers' behaviour. Therefore, in order to answer this study's research objective, it is necessary to draw from several literature domains predominately Information Systems, Industrial Marketing, and Agricultural Science. This multidisciplinary approach enriches the research by allowing a thorough examination from various perspectives, leading to a more complete examination of the research question.

1.5.2.1 Information Systems – Technology Adoption

Technology adoption is a major part of the Information Systems (IS) literature (Brown *et al.*, 2014), focusing on the antecedents to users' intention to adopt certain technologies (Taherdoost, 2018). Understanding these factors can lead to a better acceptance and usage of technology, alongside improved theoretical outputs (Lai, 2017). Venkatesh and Brown (2001) determine that there are four main theories within the literature which address acceptance: Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), Diffusion of Innovations (DoI) Theory and the Technology Acceptance Model (TAM). These theories offer well-established models to improve understanding of how and why individuals or organisations decide to adopt new technologies (Straub, 2009). Newer models such as the UTAUT from Venkatesh *et al.* (2003) also offer considerable insights regarding intentions and behaviours (Williams *et al.*, 2015). These models highlight the importance of positive perceptions and attitudes, with behavioural intention being a strong predictor of adoption (Knierim *et al.*, 2018). As such, the lens of IS literature is critical to assess the influence of socio-psychological aspects on SFT adoption.

TAM is used as the theoretical framework for the study. The model suggests that the user's perceptions regarding the ease of use and usability of the technology influences the attitude towards using the technology, their intention to use the technology and the actual usage. TAM has received considerable empirical support and is widely recognised as providing a strong theoretical basis for understanding user acceptance of technology (Yousafzai *et al.*, 2007a). It has a strong predictive power and has been validated across several contexts and environments (Venkatesh *et al.*, 2007). TAM is also flexible, allowing for the incorporation of additional variables that are relevant to specific contexts (Schepers and Wetzels, 2007). Section 2.8.5 provides an in-depth examination of these additional variables.

1.5.2.2 Industrial Marketing/ Organisational Buying Behaviour

Many studies in the extant literature have identified the farmer's behaviour as industrial or business to business (B2B) in nature, as the farmer is essentially making decisions to improve their production process (Kool *et al.*, 1997). It is, to some extent, difficult to categorise the farmer as their business objectives and personal goals often overlap (Austin *et al.*, 1998; Gasson, 1973; Sprung and Jex, 2017). However, more recently, an increasing number of farmers identify as businesspeople or entrepreneurs, moving away from the traditional producer-farmer identity (Kangogo *et al.*, 2020; McElwee, 2006; Vesala and Vesala, 2010). New production capacities, new technologies and investment opportunities, are all pushing the farmer to pay more attention to farm management decisions to drive efficiency (Vukelić and Rodić, 2014). In addition, the reform of the Common Agricultural Policy (CAP) and increased financial assistance from governments has motivated farmers to become more commercial or business-like (Morgan *et al.*, 2010). Milestad *et al.* (2012) recognise that farmers exist in an ecosystem that is constantly changing and competitive, resulting in a drive to increase revenue and gain a competitive advantage. Jayashankar *et al.* (2018) identify agricultural technology providers as having a B2B relationship with farmers, selling IoT devices and big data analysis services.

Batte (2000) determines that the purchasing behaviour on farms can be described as industrial buying behaviour or Organisational Buying Behaviour (OBB), as the farmer is purchasing products to operate their farm. OBB is described as a decision-making process, motivated by the goals of the organisation but constrained by financial, technological and human resource factors (Diba *et al.*, 2019). Although this doctoral study does not examine actual behaviour, it is contended that understanding the determinants of behavioural intention is necessary to understand the dynamics that then lead to actual adoption and SFT usage on farms. For instance, Pandey and Mookerjee (2018) explain that part of OBB is assessing products and services which then leads to the formation of behavioural intention. Annosi *et al.* (2019, p. 62) take an OBB approach in their study of technology 4.0 investment decisions by defining small to medium farms as SMEs or "*micro, small and medium firms in the agricultural industry, involved either in producing, rearing or growing agricultural products as well as harvesting, milking, breeding animals for farming purposes, for grazing or cultivation with agricultural methods*". Similarly, Groenewald (1987) describes the farmer as a business owner with decisions ultimately made by and effecting one person. Anderson (1987) deduces that although the farmer is an individual, they are making their decisions as a production manager and therefore an OBB approach is appropriate. Accordingly, it is asserted that examining the OBB literature delivers a more nuanced understanding of the organisational factors that drive the intention to adopt SFT and also highlight the importance of trust.

1.5.2.3 Psychology

As understanding the influence of psychological factors on the intention to adopt a technology is important, the psychology literature is examined. Rogers (2003) determines that individuals will adopt a technology at different stages. This can be due to the individual's personality, their attitudes to the technology and the attributes of the technology (Ramírez-Correa *et al.*, 2019; Vishwanath, 2005). Personal innovativeness in the domain of information technology, which can be described as "*the willingness of an individual to try out any new information technology"*, is recognised as an influential variable (Agarwal and Prasad, 1999, p.206). Indeed, Tey and Brindal (2012) deduce that in order for farmers to adopt SFT they must participate in behavioural change. Thus, examining the behavioural change and the psychology literature related to personality is necessary.

1.5.2.4 Agricultural Science

The domain of agricultural science is broad and multidisciplinary, encompassing a range of subjects that relate to solving problems with regard to agricultural production (Zimdahl, 2022). Falvey (2020) determines that this includes humanities, arts, social sciences and technological perspectives. Consequently, a key focus for research in agricultural science is demonstrating how new technologies such as sensors, IoT technologies, nano technology and blockchain can help increase farm productivity and sustainability (Greenwood *et al.*, 2009; Ofori *et al.*, 2020; Silva and Giller, 2021). Shepherd *et al.* (2020) call for more transdisciplinary research to determine how farmers can adopt digital technologies on farm to their advantage. As the context of this study is understanding the intention to adopt SFT, the body of agricultural science literature is drawn upon to fully understand the farmer, the farming context, and the agricultural landscape.

1.6 Thesis Outline

Following on from this chapter, a comprehensive overview of the Technology Adoption literature and Organisational Buying Behaviour is presented in Chapter 2. Detailed insights into the key factors influencing the farmer's behavioural intention to adopt SFT are offered. This centres on the farmer's perceptions and attitudes towards SFT, the personal innovativeness of the farmer, the role of social influence and the impact of trust in the SFT vendor. The review of the extant literature confirms the need for an integrated, conceptual model which addresses the shortcomings in the literature and allows for empirical verification of the factors influencing intention to adopt SFT. The following Chapter, 3, presents the integrated, conceptual model and its associated hypotheses are proposed, supported by the literature.

Chapter 4 outlines the positivistic research philosophy followed by the researcher and discusses the research design and associated methodology. The constructs used in the questionnaire are conceptualised and operationalised accordingly. This chapter also includes a detailed data analysis plan, related to the statistical analysis to be undertaken. IBM Statistical Package for Social Sciences (SPSS) AMOS 28.0 and SPSS version 26.0 were used for the structural equation modelling (SEM) and for descriptive purposes. The analysis of the data is discussed in Chapter 5. This includes reliability and validity testing, confirmatory factor analysis and SEM testing which includes initial model fit, nested models, alternative theories and mediation and moderation testing. Chapter 6 provides a discussion based on the findings outlined in Chapter 5. This discussion is contextualised by integrating the literature reviewed in Chapter 2, broadening the body of knowledge related to SFT adoption. In Chapter 7, a summary of the research process and findings are presented. The significant theoretical contributions and managerial implications are detailed, while acknowledging the limitations of the research and potential future research agendas.

1.7 Conclusion

This chapter presents a background to the research, the overarching objective of the study, its context and the research domains being examined. The next chapter builds on the background to the research presented and delivers a detailed review of the extant literature relating to technology adoption and the factors influencing the intention to adopt such technology.

Chapter 2: Literature Review

2.1 Introduction

This study examines the key internal and external factors which influence the farmer's behavioural intention to adopt Smart Farming Technology (SFT). The research examines how these factors interrelate and their associated impact on the intention to adopt SFT. This chapter provides the underlying theoretical framework for this study, focused on the Technology Acceptance Model (TAM) but also elements of Organisational Buying Behaviour (OBB). The first section commences with an overview of SFT, definitions, and categories of the technology. Next, a summary of the literature related to OBB is presented in Section 2.3. The unit of analysis in this study is the farmer, operating as a business-owner, therefore, applying an OBB perspective is valuable. This perspective can also help to identify psychological, social and economic factors that influence both the intention to adopt a technology and the final decision. Thus, the buying situation, the buying centre, and the factors impacting the decision to purchase goods or services are investigated.

Section 2.4 focuses on the buying situation which assesses whether the purchase or adoption decision is new or whether the individual or organisation is experienced. It is important to understand if the farmer has previous experience with SFT as this can influence their perceptions and attitudes. Section 2.5 considers the buying decision process and examines the factors which influence the process. OBB categorises these factors as environmental, organisational, individual, and social. Son and Benbasat (2014) outline how such factors can impact intention, adoption and usage in the workplace. Therefore, each of these categories of factors are subsequently examined in the context of SFT adoption. Next, Section 2.6 discusses the buying centre which refers to the members of an organisation who are involved in the decision-making process for a particular product or service. This section examines the influence of external actors in the farmer's network, such as peer farmers and farm advisors.

In Section 2.7, the Technology Acceptance (TA) literatures are examined to understand the factors impacting adoption of technology, particularly the socio-psychological determinants. The dominant models in the literature are discussed and the Technology Acceptance Model (TAM) is presented as a suitable model to use as a guiding lens for this study. TAM is cited as a useful model to predict technology acceptance, demonstrating results that are statistically reliable (Gupta *et al.*, 2022; King and He, 2006; Legris *et al.*, 2003; Marangunić and Granić, 2014; Schepers and Wetzels, 2007). The model considers how the perceptions and attitudes of the user shape their behavioural intention and actual usage of a technology (Davis, 1986). The final section discusses alternative frameworks considered for this research.

2.2 Smart Farming Technology (SFT)

Agriculture is facing many challenges ranging from reduced margins, constantly changing and new regulations, to growing environmental concerns (Jerhamre *et al.*, 2022). SFT can potentially overcome these challenges and benefit rural and agricultural communities. The adoption and use of such technologies can lead to improved productivity and sustainability (Kernecker *et al.*, 2019; Medvedev and Molodyakov, 2019; Regan, 2019), helping to safeguard the environment, deliver economic profitability, and ensure social and economic equity for the farmer (Adnan *et al.*, 2019). Smart farming is the use of information and communication technologies (ICT) and devices, incorporated into agricultural machinery and equipment, thereby creating large volumes of data (Pivoto *et al.*, 2018). Conversely, SFT is the range of such ICT and smart devices applied on-farm to improve the operations (Giua *et al.*, 2022). Examples of SFT include unmanned aerial vehicles (UAV) which can identify weeds and improve fertiliser application (Javaid *et al.*, 2022; Lottes *et al.*, 2017), unmanned ground vehicles (UGV) which can seed, harvest and spray autonomously (Mahmud *et al.*, 2020; Moysiadis *et al.*, 2021) and robotics which can be deployed to milk cattle and free up the farmer’s time (Driessen and Heutinck, 2014). They also include Internet of Things (IoT) technologies such as sensors to monitor soil quality and improve water management (Inoue, 2020) or wearables that monitor animal health (Neethirajan, 2020). These technologies provide farmers with data to allow them to optimise their operations and improve both yield and profit (Bacco *et al.*, 2019; Brewster *et al.*, 2017). The range of SFT is distinctly diverse and their application on farm differs according to the technology in question, the farmer and the farm context (Kernecker *et al.*, 2021). Balafoutis *et al.* (2020, p. 2) and Kernecker *et al.* (2021) broadly classify SFT into three categories: 1) farm management information systems (FMIS) that manage data to support farm operations 2) precision agriculture (PA) systems and GNSS (global navigation satellite systems) and 3) automated systems such as robotics and artificial intelligence. Ofori *et al.* (2020, p. 648) further divide these technologies into ‘embodied knowledge technologies’ which require little training to operate and 'information intensive technologies' which need upskilling or training by the farmer to fully benefit from the data produced.

This trend of moving towards data-driven agriculture has been described using several names; precision agriculture (PA), digital farming, smart farming and Agriculture 4.0, which are often used interchangeably (Klerkx *et al.*, 2019; Paraforos and Griepentrog, 2021; Saiz-Rubio and Rovira-Más, 2020). Agriculture 4.0 is the term for the fourth revolution in agriculture, signifying a move towards digital technology implementation not only in farming, but also in agricultural logistics and storage (Javaid *et al.*, 2022). Shang *et al.* (2021) determine that digital farming and smart farming are the same concept, relating to the use of digital technologies on farm. PA is defined as a strategy using electronic technologies to improve and optimise the efficiency, productivity and sustainability of agricultural processes (Lowenberg-DeBoer and Erickson, 2019). For example, pesticides and fertilisers can be applied precisely to an exact location minimising the level used and thereby lessening the farmer's environmental footprint but also saving both time and money (Walter *et al.*, 2017). However, smart farming goes further than PA by "*basing management tasks not only on location but on data, enhanced by context and situation awareness, triggered by real-time events*" (Sundmaeker *et al.*, 2016, p. 133). Although PA technologies (PAT) differ slightly to SFT, the lack of studies on SFT adoption often results in the lessons learnt from PAT adoption studies being applied to the SFT domain (Shang *et al.*, 2021), as is the case in this research.

SFT and PAT have the potential to revolutionise agriculture more than mass farming methods did in previous years (PwC, 2018). However, Gargiulo *et al.* (2018) and Eastwood and Renwick (2020) note that the widespread adoption of such technologies has been slow. Furthermore, adoption of SFT is not without risk and can, in some instances, negatively impact the farmer, their animals and society (Regan, 2019). Division already exists in the farming community based on the size of farm (big vs small), location (urban vs rural) and characteristics of the farmer (age, education level and income) (Fleming *et al.*, 2018). Technology adoption furthers this divide with Bronson (2019) highlighting the need to ensure that SFT is accessible to all farmers and farm types. Rossi Borges *et al.* (2019) state that understanding farmers' decisions regarding the adoption of agricultural innovations is important. Furthermore, Annosi *et al.* (2019) determine that understanding how and why agricultural SMEs adopt digital technologies is central to a successful adoption process. In their study, agricultural SMEs were defined as businesses involved in "*producing, rearing or growing agricultural products as well as harvesting, milking, breeding animals for farming purposes, for grazing or cultivation with agricultural methods"* (Annosi *et al.*, 2019, p. 62) and later referred to as farms. These studies outline the distinct need to examine the key influences of farmers' intentions to adopt SFT.

2.3 Organisational Buying Behaviour (OBB)

Farmers are increasingly under pressure to ensure optimal business management on their farms, reducing costs and improving outputs (Sok *et al.*, 2020). Moreover, the introduction of digital technologies on-farm has introduced new business models which the farmer must develop expertise in (Klerkx *et al.*, 2019). However, Mitchell *et al.* (2021) discuss how farmers often have to prioritise the generation of farm income over learning about new technologies and agricultural processes. Although, the Technology Acceptance Model (TAM) is used as the main theoretical framework for this research, it is posited that using an OBB lens to understand the intention of the farmer, as a business owner, to adopt SFT is also beneficial. OBB is defined as the decision-making process an organisation or a business undertakes which establishes the need for a product, searches and evaluates providers, selects a supplier, and manages the order for purchase (Webster and Wind, 1972). Lord *et al.* (2010) and Elser and Michael (2023) argue that the intention to adopt or purchase a technology is part of the process. Therefore, within a business setting, understanding the intention to adopt an innovation is central to a successful adoption process (Annosi *et al.*, 2019).

Much of the theory around OBB is grounded in the seminal work of Robinson *et al.* (1967), Webster and Wind (1972) and Sheth (1973). These authors are recognised as developing the first deductively based models in the domain of industrial marketing (Wilson, 1996). Initially, these models were focused on large industrial organisations but more recently they are considered relevant to all organisations (Wilson, 2000). The models are praised for their generality (Ward and Webster, 1991) but are recognised as lacking a conclusive overview of all variables, concepts and relationships involved in the buying process (Johnston and Lewin, 1996). The following section provides a brief overview of each of the seminal models.

2.3.1 Seminal Models of OBB

2.3.1.1 BuyGrid Model

One of the first models in the OBB domain was the BuyGrid model from Robinson *et al.* (1967) which emerged from an exploratory study of industrial and electronic firms (Wind and Thomas, 1996). The model suggests that three dimensions of OBB must be understood; the buying situation, the buying process, and the buying centre. Steward *et al.* (2019) deduce that the BuyGrid model delivers a succinct understanding of OBB by highlighting that the purchase or buying situation will impact the buying process. Thus, understanding whether or not the farmer has previous experience with SFT is necessary to examine. Section 2.4 examines the buying situation in more detail.

2.3.1.2 Model for Understanding Organisational Buying Behaviour

Webster and Wind (1972) proposed a general 'Model for Understanding Organisational Buying Behaviour' building on the work of the BuyGrid model. They deduce that the decision-making process is conducted by an individual in the organisation but in connection with others, known as the buying centre. In relation to agriculture, the individual farmer is ultimately the decision maker. However, Rose *et al.* (2018b) recommend that research moves away from focusing on the farmer as an individual and instead concentrates on determining how other actors in the network impact the decision. Understanding how influential others in the farmer's network impact the intention to adopt SFT is thus detailed further in Section 2.6. Furthermore, the model from Webster and Wind (1972) suggests that four types of factors, namely environmental, organisational, social, and individual, influence the organisation's perceptions, attitudes and subsequent buying behaviour. These factors are outlined in more detail in Section 2.5.

2.3.1.3 Integrative Model of Industrial Buyer Behaviour

Following the criticism of the BuyGrid model and the Model of Organisational Buying Behaviour, Sheth (1973) proposed a more intricate model: the Integrative Model of Industrial Buying Behaviour. This model analyses the psychological constructs which impact the buying process (Ward and Webster, 1991). He argues that the expectations of individuals within the buying centre of the organisation are influenced by several criteria including personality. Thus, the individual's personality is a noteworthy variable to examine further, as outlined in Section 2.8.5.2.

2.3.2 Developments in OBB Theory

With newer OBB models lacking, it is argued that elements of the classic organisational buying models from Robinson *et al.* (1967), Webster and Wind (1972) and Sheth (1973) are still relevant today. In their bibliometric analysis of industrial/organisational buying research, Chavan *et al.* (2019) deduce that from 1990, the number of studies focusing on OBB levels off, but new constructs such as trust, relationships, segmentation and risk have been introduced in the literature. Dilleen *et al.,* (2023), van der Burg *et al.* (2019) and Wiseman *et al.* (2019) explain that trust in the SFT vendor is important in terms of encouraging farmers to adopt SFT. Consequently, trust is examined comprehensively in Section 2.8.5.3. Although these seminal or classic models were developed by different authors, they focus on similar constructs which are subsequently examined further, namely: the buying situation, the factors influencing the decision-making process and the buying centre.

2.4 The Buying Situation

The buying situation influences how straight-forward or extensive the farmer's efforts are in the buying process (Kool *et al.*, 1997). Three types of buy classes or buying situations exist: new tasks, modified rebuy and straight rebuy (Robinson *et al.*, 1967). These classifications are broadly accepted in research studies and textbooks (Wilson, 2000). New tasks situations are seen as complex and often relate to a first-time buyer. In these situations, price is not always the main decision driver, but meeting the organisation's needs is key (Robinson *et al.*, 1967). A modified rebuy is when an organisation is replacing or modifying an existing product and, thus, classified as lower risk (Zinszer, 1997). A straight rebuy is a re-order of existing products and is straight forward (Polonsky *et al.*, 1998).

Kernecker *et al.* (2019) and Soto *et al.* (2018) highlight that there are likely to be several differences in the adoption process of farmers who have experience with SFT and non-adopters. Jakku and Thornburn (2010) conclude that adopters and non-adopters have different beliefs and expectations in terms of the outcomes delivered by adopting technology. Watcharaanantapong *et al.* (2014) establish that the decision to adopt SFT is influenced by whether the farmer has at least one SFT already in place. For example, farmers that use variable rate technology are more likely to adopt yield mapping technologies due to the complementary nature of the technologies (Isgin *et al.*, 2008). Similarly, Michels *et al.* (2020b) deduce that if the farmer has experience of using SFT, they could adapt their skills to use other technologies and therefore the decision-making process is not as difficult. This suggests that non-adopters and adopters will have significant differences in their perceptions of the technology and their subsequent intention to adopt SFT. Certainly, much research focuses on the characteristics of the innovation and the adopter itself, but few have explored the attitudes and motivations of both adopters and non-adopters (Rehman *et al.*, 2007). Thus, it is important to understand the SFT adoption situation as this will influence both the farmer's perceptions and intention. The next section provides a discussion on both of these elements.

2.5 Buying Decision Process & Influencing Factors

The buying decision process refers to the different stages in the process namely: problem identification, establishing the required specifications, identifying alternatives, evaluating alternatives and selection (Steward *et al.*, 2019). Given that the scope of this study is to examine the intention to adopt SFT, an investigation of the farmer's buying process falls beyond the research objective. However, as previously outlined, Sun *et al.* (2020) and Webster and Wind (1972) determine that organisational, social, individual, environmental and technological factors influence organisations' intention to adopt technologies and strategies. In a farming context, Osrof *et al.* (2023) categorise influential factors as individual, organisational, technological and external, as discussed in more detail below.

2.5.1 Environmental influences

An organisation functions within the wider context of the environment in which it operates. Environmental influences consist of physical, technological, economic, political, legal and cultural factors and are exerted from a variety of sources, including the government, trade associations, legal representatives, professional groups, suppliers, competitors and customers (Palanisamy *et al.*, 2010). With regard to SFT, tax incentives and government subsidies are proven to be a positive influence on adoption (Bacco *et al.*, 2019; Barnes *et al.*, 2019a; Knierim *et al.*, 2018). The impact of Covid-19 on the agricultural sector must also be considered, as it could have potentially driven interest and urgency in SFT adoption. Di Vaio *et al.* (2020) highlight how technologies such as Artificial Intelligence (AI) could be a support to farmers and agri-businesses, particularly with any labour shortages such as during the Covid-19 crisis. Physical factors relate to the geographic location of the organisation as well as ecological or climate-related issues which may influence the decision (Webster and Wind, 1972). Examining all environmental factors and how they influence the farmer's behavioural intention to adopt

SFT is not feasible for this study. While sustainability concerns related to the future of agriculture are of central importance to the farmer, Knierim *et al.* (2018) and Kernecker *et al.* (2019) determine that farmers are not convinced on how SFT benefits the environment. Furthermore, as the objective of this research is to create a model which is generalisable across different contexts, including the perceptions of the environmental benefits related to SFT may limit the model's applicability in varied settings. Consequently, the focus of this research is on organisational, social and individual influences.

2.5.2 Organisational influences

Aubert *et al.* (2012) determine that the adoption of precision agriculture technologies (PAT) is a strategic decision which has long term implications for the farm. This is supported by Cavicchi and Vagnoni (2018) who state that the decision to adopt these technologies is a strategic move to improve the competitiveness of the farm. Furthermore, Huffman (2020) outlines how the decision to adopt a new technology can be classified as an investment decision as there are significant costs associated with learning and adopting the technology, with the return on investment only apparent over time. Therefore, the size of the business, how established it is, the existing knowledge within the organisation, knowledge exchange functionalities, the readiness to change, and the existence of clear objectives and goals impact technology adoption decisions (Greenhalgh *et al.*, 2004). Although firms operate in a similar environment, how they respond to challenges determines their success; often referred to as their strategic orientation or strategies to achieve a sustained competitive advantage (O'Regan and Ghobadian, 2005). This strategic orientation is related to the capacity for innovation and learning within the organisation (Hakala, 2011). As with other organisations, farms and farmers differ in their level of strategic and entrepreneurial orientation and capabilities (McElwee and Smith, 2012). This is due to external factors such as farm size, farm type and location (Das *et al.*, 2019) and internal factors such as the entrepreneurial identity, attitude and innovativeness of the farmer (Vesala, 2008). As such, it can be suggested that farmers need to develop a positive attitude towards using new innovations to allow them to develop their farms. However, this is influenced by the farm type and farm size which are subsequently discussed.

2.5.2.1 Farm size

The literature is conclusive in determining that farm size influences technology adoption decisions, due in part to the considerable cost associated with adoption (Blasch *et al.*, 2022). Larger farms have more access to capital and a higher borrowing capacity than small scale farmers (Lawson *et al.*, 2011) and therefore can afford the investment associated with technology adoption (Tamirat *et al.*, 2017). However, farms below 100 hectares (ha) and with an income of less than 25,000 EUR, find it difficult to access SFT (Dryancour, 2017). In their critical review of adoption of innovation in agriculture, Rossi Borges *et al.* (2019) determine that farm size is one of six variables that has a significant effect on technology adoption more often than not. The other factors cited include irrigation, slope, distance from the farm to home, participation in training or on-farm demonstrations, and membership of a farming association. Those with larger farms and therefore a larger farm income, are more likely to invest in and adopt SFT (Daberkow and McBride, 2003; Das *et al.*, 2019; Kutter *et al.*, 2011; Schimmelpfennig, 2016). Such large farms benefit from economies of scale associated with SFT usage (Pierpaoli *et al.*, 2013) and can absorb some of the risk associated with investing in the technology (ibid). This leads Kernecker *et al.* (2019) to suggest that perhaps it is not the landmass but the economic size of the farm which is the influencing factor on intention and adoption.

Bjornlund *et al.* (2009) and Caffaro and Cavallo (2019) find that farmers with smaller parcels or land-masses are less likely to consider adopting technology. Such small-scale farmers are also less likely to value the associated benefits of SFT implementation than larger scale farmers. Consequently, much SFT has been developed with the larger farm in mind, alienating the small farm business (Fleming *et al.*, 2018). This is important as Pindado and Sanchez (2017) deduce that small-scale farming is central to European agriculture. However, Knierim *et al.* (2019) outline that both farmers and experts in the field of SFT propose that the size and scale of a farm will no longer be a significant influencer as technologies become more flexible and adaptable. Mizik (2022) further proposes that the modularity of SFT might make it more accessible to smaller-scale providers, but that clearly demonstrating the usability of the technology and value of adoption is critical. Additionally, Pierpaoli *et al.* (2013) determine that there is a positive correlation between farm size and the attitude to using PAT. Schukat and Heise (2021a) deduce that farm size is a moderating factor on the relationship between social influence and intent as well as technology readiness and intention. This suggests that farm size may be a moderating factor rather than a mediating factor.

2.5.2.2 Farm type

The farming context or farm type affects the speed of technology adoption with arable and viticulture more prevalent adopters than animal-based farming (Borchers and Bewley, 2015). Similarly, Barnes *et al.* (2019a) find that farms predominately consisting of arable land are more likely to adopt PAT. This is correlated with the size of the farm (Kernecker *et al.*, 2019) but also additional factors. For example, farmers involved in tillage have a higher requirement for data which positively impacts their adoption decision. On the other hand, livestock farming is less flexible and the adoption of relevant digital technologies such as robotic milkers can require significant investment and changes to existing structures (Groher *et al.*, 2020). While acknowledging that farm type is an influential factor in the intention to adopt SFT, it has been excluded from the scope of this study. This is based on the overarching objective of the research to focus on the broader determinants that influence the intention to adopt SFT, rather than the specifics associated with farm type.

2.5.2.3 Farm location

The location of the farm influences the adoption decision due to the technological infrastructure in place (Ronaghi and Forouharfar, 2020). Rural areas often struggle with the lack of connectivity, limiting the choice of SFT which can be applied on-farm (Bacco *et al.*, 2019). The quality of the land also impacts adoption decisions as farmers that deem their land to be good quality are more favourable to considering adopting PAT (Shang *et al.*, 2021). Furthermore, Asheim and Gertler (2005) determine that the distribution of innovations is not equal across the world, with clusters of innovative activity occurring in certain locations. The existence of innovative clusters/hubs or regional innovation systems are key to sharing tacit and explicit knowledge (ibid). As such, farmers may learn from localised experts or extension services when considering their technology adoption decisions (Knierim and Prager, 2015). Although location and region are important to consider, the diverse perspectives among farmers related to land quality (Bicalho and Peixoto, 2016; Wang *et al.*, 2022) are too extensive to allow for a comprehensive examination in this research. Thus, location as a variable of interest is excluded in this study.

2.5.2.4 Culture

According to Leidner and Kayworth (2006), culture has a major influence on both individuals and organisations. Pertinently, ICT adoption and its efficiency are influenced by national culture and the culture of an organisation. Hofstede *et al.* (2010, p. 6) defines culture as "*the collective programming of the mind which distinguishes the members of one human group from another"*. This has a major influence on how a society behaves and thinks (Gerlach and Eriksson, 2021). Several researchers have thus determined that is important to understand the influence of culture when assessing technology adoption (Huang *et al.*, 2019; Straub *et al.*, 1997). Knook and Turner (2020) determine that culture in farming consists of the farmer's values, beliefs or attitudes and their practices. For example, the culture in agriculture across Western countries is mostly preoccupied with protecting the family farm and also maximising food production (Inman *et al.*, 2018; Knook and Turner, 2020). O'Shaughnessy *et al.* (2021) outline how cultural practices shape smart farming practices and alternative solutions. Furthermore, Tanko and Ismaila (2021) determine that culture influences how the farmer can access credit and various agriculture inputs, thus having an impact on technology adoption. Due to the multifaceted nature of culture, an in-depth analysis of how cultural factors impact SFT adoption extends beyond the scope of this study.

2.5.3 Social /Interpersonal influences

Social influences correspond to how individuals within the organisation and the buying centre influence the buying decision (Webster and Wind, 1972). In an agricultural context, this relates to how the farmer's network influences their perceptions of technology, their attitudes and the behavioural intention to adopt. This is examined further in Section 2.6.

2.5.4 Individual influences

Power in OBB is attributed to the individual at the centre of the buying task and buying centre rather than the organisation (Meehan and Wright, 2012). Accordingly, in most social research, the individual is the typical unit of analysis (Babbie, 2014). In the context of intending to adopt SFT, this is the individual farmer and thus the unit of analysis in this study. Webster and Wind (1972) determine that the individual's personality, their motivations, risk preferences, their ability to learn and how they learn influences their perceptions, responses and behaviour. As outlined in Section 2.3.1, Sheth (1973) places considerable importance on understanding the psychology of the individual making the decision within the organisation. In addition, Meijer *et al.* (2014) determine that personal characteristics of the farmer such as age, gender, education and confidence all impact the SFT adoption decision.

An individual's level of trust in technology and in the technology supplier can also impact the adoption decision (Yousafzai *et al.*, 2010). Trust is an important concept in B2B relationships which helps to allay buyer concerns, reduce vulnerability, and improve long-term relationships (Allen and Wilson, 2003; Bhattacherjee, 2002; Kemp *et al.*, 2018). In complex buying situations within an organisation, the decision-maker will rely on trust to help reduce uncertainty (Osmonbekov and Johnston, 2018). Consequently, trust has become a key focus in business research particularly examining buyer-seller relationships (Blomqvist, 1997; Li and Betts, 2003). Following on from this, several of the most cited individual influences such as age, gender, education, personality and trusting beliefs are further discussed in Section 2.8.5.

2.6 Buying Centre & Social Influence

The buying centre is the group of individuals in an organisation who are collectively responsible for gathering relevant information related to the purchase of a product, making recommendations and ultimately the buying decision (Johnston and Lewin, 1996; Webster and Wind, 1972). Järvi and Munnukka (2009) describe the buying centre as a buying network or decision-making unit (DMU) where individuals from different backgrounds and expertise join up to share knowledge and lessen the risk associated with a buying or adoption decision. It is argued that the farmer does not have a traditional buying centre, as described in OBB by Webster and Wind (1972), but does however consult with members of their network before adopting new technologies (Blasch *et al.*, 2022; Caffaro *et al.*, 2020). Fountas *et al.* (2006) outline how several actors in the network influence the farmer's decision-making including a) the decision maker; the person who is responsible for making the decision, b) participants; people who assist the decision-maker with their decision and, c) influential people; people who have either expertise or power to influence the decision. Thus, these actors can be established as: a) the farmer, b) peer farmers and farm family members and, c) farm advisors and farming organisations. Critically, Shang *et al.* (2021) find that the influence of the farmer's social network on their technology adoption decisions has not been a key focus in empirical studies. This is further examined in Section 2.8.5.1.

The previous sections used the lens of OBB to determine the factors influencing the farmer's behavioural intention to adopt SFT. This included the buying situation and whether the farmer was a non-adopter or had previous experience with SFT. Next, factors influencing the organisation's decision-making process were discussed, such as organisational factors related to farm size and trust in B2B relationships, and individual influences such as personality. Finally, the influence of the buying centre or social influence on the farmer's technology adoption decision were addressed. As detailed, although OBB focuses on the decision-making process to purchase a technology or product, it is argued that intention is an important step in the process. The subsequent section presents an overview of the Technology Adoption (TA) literature, focusing in detail on the Technology Acceptance Model (TAM) as the main theory used for this research. Each of the constructs in TAM are discussed, alongside factors highlighted in the OBB literature as impacting the behavioural intention to adopt a product or service.

2.7 Technology Adoption

Several studies of farmers' technology adoption decisions acknowledge the benefits of combining multiple models and dimensions to understand the process (Aubert *et al.*, 2012; Greenhalgh *et al.*, 2004; Tey and Brindal, 2012). However, many of the existing models addressing farmer's behaviour are based on the assumption that the farmer's main aim is to drive profit (Migliore *et al.*, 2014) and hence focus on the economic drivers of farmers' technology adoption decisions such as cost and investment opportunity (Long *et al.*, 2016). Although farmers are interested in profit maximisation, cost-benefit models do not always explain the farmer's intentions and behaviour sufficiently (Caffaro *et al.*, 2019). Knierim *et al.* (2019) highlight that many of the studies on technology adoption fail to examine the farmer's attitude, perceptions, and interest in technology. It is therefore acknowledged that using psychological constructs such as attitudes, values, perceptions, motivations can help to predict behaviour (de Lauwere *et al.*, 2020; Migliore *et al.*, 2014; Unay-Gailhard and Bojnec, 2016). Consequently, the lens of Technology Adoption (TA) as part of the Information Systems (IS) literature is critical to assess the influence of socio-psychological aspects on technology adoption.

The discipline of IS focuses on understanding the "*implementation, adoption, and use of new or updated systems*" (Tatnall, 2009, p. 1). Understanding the factors that impact adoption can lead to a more successful uptake of technologies (El-Gohary, 2011). Aubert *et al.* (2012) highlight the overall lack of IS research in the agriculture sector, with studies more likely to focus on the manufacturing, IT, banking, or retail sector. Several theories of technology adoption exist within this IS literature including the Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), Diffusion of Innovation Theory (DoI) and Technology Acceptance Model (TAM) (Oliveira and Martins, 2011). Venkatesh *et al*. (2003) also subsequently introduced the Unified Theory of Acceptance and Use of Technology (UTAUT) to explain users' intention to use an information system. These key theories relating to human behaviour and technology adoption are thus reviewed.

2.7.1 Theories of Behavioural Change and Adoption

As outlined, several theories of behavioural change and/or adoption exist. Table 2.1 outlines the main theories, the variables measured, and the key criticisms associated with each of the theories/models and therefore why they are not adopted in this study. The Theory of Reasoned Action (TRA) from Fishbein and Ajzen (1975) has been described by Venkatesh *et al.* (2003) as one of the most influential theories of human behaviour. The theory seeks to understand how and why individuals are persuaded to behave in a certain manner. It posits that a person's attitude and subjective norms (perceived social pressure to behave in a certain way) influence the intention to carry out a behaviour. This behavioural intention has a direct influence on actual behaviour. Thus, TRA was one of the first theories that revealed a link between attitude and actual behaviour (Burton, 2004). The biggest criticism of the TRA is the assumption that the individual has volitional control over the behaviour, which is not always the case, and thus led to the development of the Theory of Planned Behaviour (TPB) (Sok *et al.*, 2020).

The TPB from Ajzen (1991) seeks to predict and explain the behaviour of an individual within a certain context (de Lauwere *et al.*, 2020). It is an extension of TRA, using the constructs of attitude and subjective norms, but introduces a new construct of perceived behavioural control (PBC) (Venkatesh *et al.*, 2003). PBC relates to the individual's perception of their ability to perform the behaviour and is important in situations where the behaviour requires a certain set of skills or knowledge (Ajzen, 1991). Like the TRA, the TPB is not without fault. Burton (2004) deduces that within an agricultural context, the TPB insufficiently explains and predicts the factors which influence farmers' behaviour. Crucially, Ajzen (2020) highlights that the theory is general, whereas the Technology Acceptance Model (TAM) is specifically related to the acceptance of a technology. TAM provides guidance on the factors which influence acceptance and thus reliability and validity of these constructs can be ascertained. Specifically, TAM is deemed a more suitable framework to understand the farmer's decision to consider adopting SFT.

In addition to the theories outlined above, the Diffusion of Innovation Theory (DoI) from Rogers (1962) and the Unified Theory of Acceptance and Use of Technology (UTAUT) from Venkatesh *et al.* (2003) have also been used to explain adoption of technologies in certain contexts. DoI has been used to explain how new innovations are adopted by individuals and populations over time (Rogers, 2003). The model was developed based on the work from Ryan and Gross (1943) relating to their study on hybrid seed corn adoption among Iowa farmers. However, its major criticism relates to the theory helping to conceptualise adoption, rather than predicting it (Kuehne *et al.*, 2017). UTAUT focuses on four constructs namely performance expectancy, effort expectancy, social influence, and facilitating conditions which are deemed direct determinants of behavioural intention. The effect of each of these constructs is moderated by age, gender, level of experience and voluntariness of use. The theory was developed following a review of eight seminal models (TRA, TPB, TAM, DoI, Social Cognitive Theory, Motivational Model, Model of PC utilisation and combined TAM/TPB) related to behaviour and adoption. Although a comprehensive model, it is criticised for being unnecessarily complex (Bagozzi, 2007a) and underperforms in real-life settings (Dwivedi *et al.*, 2011). These models are further critiqued in Section 2.9.

The main behavioural change models are reviewed in Table 2.1 below.

Table 2.1 Key Theories addressing Behavioural Change/Adoption

Theory/Model	Author/ Year	Variables	• Key Findings	Criticisms
Theory of Reasoned Action (TRA)	Fishbein and Ajzen (1975)	- Attitude - Subjective Norm - Behavioural Intention - Actual Behaviour	• Human behaviour is influenced by Behavioural Intention (BI). This is influenced by the individual's attitude and subjective norm.	Assumes that the individual has volitional control over the behaviour (Sok *et al.*, 2020).
Theory of Planned	Ajzen and Fishbein (1980)	- Attitude toward the Behaviour	• Behaviour is influenced by Behavioural	It is a general model and therefore

Theory/Model	Author/ Year	Variables	• Key Findings	Criticisms
Behaviour (TPB)		- Subjective Norm - Perceived Behaviour Control - Intention - Behaviour	Intention (BI) which is affected by the attitude toward the behaviour, the subjective norm and perceived behavioural control.	difficult to measure and test. Attitude is not explained particularly well. TAM is a more appropriate model when attitude is of interest (Mathieson, 1991).
Diffusion of Innovation Theory (DOI)	Rogers (1962)	- Relative Advantage - Complexity - Trialability - Observability - Compatibility	• The adoption decision is made up of five stages (knowledge, persuasion, decision, implementation, and confirmation). • The characteristics of the technology (relative advantage, compatibility, complexity, trialability and observability) impact this adoption process.	Helps to conceptualise adoption, rather than predicting adoption (Kuehne *et al*., 2017). Only Relative Advantage, Compatibility and Complexity have a relationship with adoption (Agarwal and Prasad, 1999). Fails to provide evidence on how an attitude toward the technology is formed in the adoption/rejection phase (Chen *et al.*, 2002). Focuses more on the characteristics

Theory/Model	Author/ Year	Variables	• Key Findings	Criticisms
				of the technology rather than attitude toward a technology (Mohr and Kühl, 2021).
Unified Theory of Acceptance and Use of Technology (UTAUT)	Venkatesh *et al.* (2003)	- Performance Expectancy - Effort Expectancy - Social Influence - Facilitating conditions - Behavioural Intention - Usage Behaviour (Moderators: Gender, Age, Experience, Voluntariness of use).	• Usage is influenced by Behavioural Intention. • Performance Expectancy, Effort Expectancy, Social Influence are direct determinants of Behavioural Intention. • Facilitating conditions directly impact Usage. • Experience, Voluntariness, Gender, and Age moderate the relationship between the direct determinants outlined and BI.	Criticised for being unnecessarily complex (Bagozzi, 2007a) and underperforms in real-life settings (Dwivedi *et al.*, 2011). Although heavily cited, the theory is not used as frequently in empirical settings (Williams *et al.*, 2011). Variance-explained level of acceptance does not rise above other models, unless pooled across three periods (Devolder *et al.*, 2008). Attitude is not included as a construct.

The next section focuses on TAM and details each of its constructs. Additional extension variables namely personality, trust, and social influence are also discussed following an analysis of the literature, as previously outlined in Sections 2.4-2.6.

2.8 Technology Acceptance Model (TAM)

The TAM devised by Davis (1986) is recognised as one of the most influential, robust and valid theories to understand the adoption and use of new technologies (El-Gohary, 2012; Granić and Marangunić, 2019; King and He, 2006; Sun and Zhang, 2006). It is a social psychology theory (Dishaw and Strong, 1999) that uses belief sets that are generalisable to various IT systems and user populations (Mathieson, 1991). It is centred on the behavioural attitudes towards a technology (Venkatesh and Davis, 2000) and captures the user's motivation, both cognitive and affective aspects, to use a technology (Davis, 1986). Venkatesh (2000) determines that TAM is one of the most parsimonious models to explain an individual's adoption of technology. It is cited as being IT-specific with a strong theoretical base (Yousafzai *et al.*, 2007a). Studies have shown that the model has a high explanatory power (Schepers and Wetzels, 2007) and is successful in predicting approximately 40 percent of the variance in the use and behaviour intention of individuals (Legris *et al.*, 2003). Similarly, Venkatesh and Davis (2000) determine that TAM is more favourable than TRA and TPB. It has considerable empirical support and has been cited over 5,000 times since its introduction (Venkatesh and Bala, 2008) and is particularly relevant when studying individual adoption where individual differences are significant (Lu *et al.*, 2005; Venkatesh and Morris, 2000).

TAM has its limitations and it has been suggested that researchers need to extend the model outside its original confines (Benbasat and Barki, 2007). However, it is credited as the dominant model to understand acceptance and adoption of various technologies (Venkatesh *et al.*, 2007) across both individual users and organisations (Hu *et al.*, 1999). For example, Dahnil *et al.* (2014) outline how TAM is effective in investigating TA across business organisations. By focusing on the key decision-maker within a business, the explanatory power of TAM increases and this overcomes some of the weaknesses associated with model (Hernández *et al.*, 2008). Thus, the focus on the farmer as the unit of analysis in this study. TAM has been used to explain adoption of new technologies in several B2B or industrial settings (Avlonitis and Panagopoulos, 2005; Jones *et al.*, 2002; Lee and Park, 2008; Schillewaert *et al.*, 2005; Siamagka *et al.*, 2015; Venkatesh and Bala, 2008) and also in an agricultural context (Aubert *et al.*, 2012; Caffaro *et al.*, 2020; Naspetti *et al.*, 2017). Certainly, Pierpaoli *et al.* (2013) determine that TAM is a suitable theory to understand the farmer's attitude to adopting technology. Consequently, TAM is deemed most appropriate for this study as it is less general than the TRA and, as outlined by Davis (1989), it is focused on the use of ICT. TAM however neglects to include some important extension variables such as the internal and external factors which may impact adoption (Yousafzai *et al.*, 2007b). Thus, incorporating variables such as personality, trust and social influence addresses this deficiency.

TAM, outlined in Figure 2.1, was originally developed to predict an individual's acceptance of computer technology in the workforce and was adapted from the TRA (Ajzen, 2020; Davis *et al.*, 1989). The scales are robust, and the relationships hypothesised in the model are proven to be true in many empirical studies (King and He, 2006; Venkatesh *et al.*, 2007).

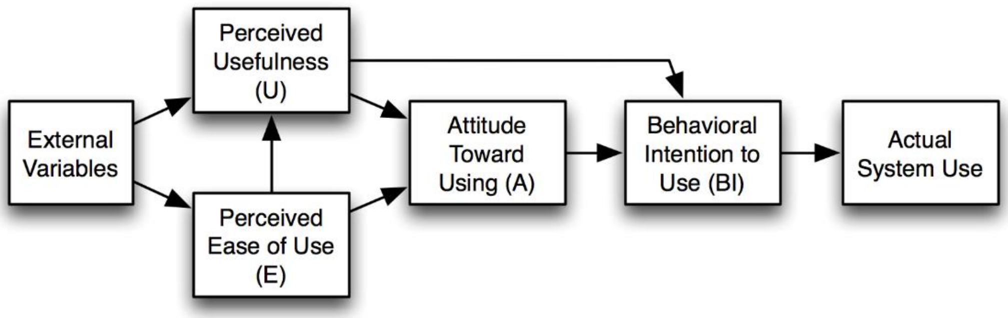

Figure 2.1 The Technology Acceptance Model (Davis, 1986)

The model posits that the attributes of a technology impact the individual's perception of the said technology through two variables: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Godoe and Johansen, 2012). PU and PEOU are deemed cognitive constructs (Raes and Depaepe, 2019), while their measures are seen as highly reliable and relevant in several contexts (King and He, 2006). These beliefs create an attitude towards using the system which is hypothesised as a major determinant of the intention to use technology and actual usage (Davis, 1986). As mentioned, TAM has received extensive criticism within the extant literature. Bagozzi (2007a) highlights how trust and other variables have not been assessed as underlying structures which explain TAM. Furthermore, Mathieson (1991) explains how TAM does not include any social variables. In their meta-analysis of TAM, Lee *et al.* (2003) underline the need to incorporate more external variables particularly social influence and personality differences. Sun and Zhang (2006) recommend adding moderating factors that represent organisational factors, technology factors and individual factors. This is similar to Wu and Lederer (2009) who determine that individual differences such as age, gender and education play an important role as moderators in TAM. Each of the constructs in TAM are now explained in further detail.

2.8.1 Behavioural Intention (BI)

The dependent variable in TAM is actual usage of a technology, which relates to the individual actually adopting and using the technology in question (Davis, 1986). Examining actual use as the dependent variable in this study was not possible due to the limitations of time and access, and the need for a longitudinal lens. Thus, behavioural intention (BI) is the dependent variable, which is recognised as being a key determinant of actual usage (Dwivedi *et al.*, 2011; Fishman *et al.*, 2018; Sheeran, 2002; Webb and Sheeran, 2006; Yi and Hwang, 2003). Venkatesh *et al.* (2003) determine that the role of intention as a significant predictor of actual behaviour is critical. This relationship has been tested and verified in several contexts such as online shopping, commercial software, internet banking and management information systems (Ozbek *et al.*, 2014; Taylor and Todd, 1995; Venkatesh and Morris, 2000). Certainly, in most prominent TA models, the relationship between antecedent variables and actual use is mediated by BI (Venkatesh and Bala, 2008). The more intent a person has towards carrying out the behaviour, the more likely they are to engage in the behaviour. Thus, BI which is defined as an individual's assessment of the probability that they will perform the behaviour, is significant to investigate (Ajzen, 1991). Warshaw and Davis (1985) define it as the degree to which an individual develops a conscious effort to carry out a particular behaviour. In the context of this study, BI therefore relates to the intention to adopt SFT.

BI is cited as explaining more variance in an individual's behaviour than other socio-demographic or psychological constructs such as attitude, social influence or personality (Fishman *et al.*, 2020). It was first developed from the TRA from Fishbein and Ajzen (1975) where it is determined by attitude towards the behaviour and the subjective norms. The theory reasoned that people tend to have a strong intention to perform a behaviour if they have a positive attitude towards it and if they feel that people important to them would look on the behaviour favourably (Sutton, 2001). The TRA thus extensively describes the positive relationship between intention and actual use (Fishbein and Ajzen, 1975). Intrinsically, intention is seen as representing motivational factors which are related to the behaviour (Ajzen, 1991). BI in the TPB is also presented as an antecedent to actual behaviour and is influenced by attitude and subjective norms but also the concept of PBC (Netemeyer *et al.*, 1993), as outlined in Section 2.8. Conversely, three conditions are necessary for BI to accurately predict behaviour: 1) the intention and actual behaviour measures must be similar in terms of target, action and context, 2) the intention must remain consistent from the time of BI to the assessment of behaviour, and 3) the behaviour under examination is under the volitional control of the individual (Fishbein and Ajzen, 1975).

TAM demonstrates a high correlation between intention and actual usage (Davis, 1989). It is posited that BI is determined by attitude and the perceived usefulness of the technology and is closely linked to actual behaviour (Davis, 1986; Davis *et al.*, 1989; Taylor and Todd, 1995). The intention is formed as a result of an individual's decision-making processes and perceptions (Venkatesh *et al.*, 2003). Davis (1986) determines that BI is an important variable as it is a better predictor of actual behaviour than attitude. The final TAM dropped attitude as a construct to deliver a more parsimonious model and instead determined that the perceived usefulness (PU) of the technology and the perceived ease of use (PEOU) created the behavioural intention towards adopting the technology (Davis *et al.*, 1989). If the technology is easy to use, it is likely that the intention to use the technology will be strong (Davis, 1989). Furthermore, if technology developers can demonstrate the effectiveness of their products and their user-friendliness, they could have better control over users' beliefs and subsequent intention to adopt the technology (Shroff *et al.*, 2011). However, further analysis of TAM revealed that the effect PEOU has on BI is mainly through PU (King and He, 2006).

Within an agricultural context, Ronaghi and Forouharfar (2020) determine that there is a positive relationship between BI and actual use of Internet of things (IoT) among farmers. Giua *et al.* (2022) outline that farmers' intentions to use SFT is influenced by their expectations on what the technology will deliver, their attitude towards SFT as well as social influences.

2.8.2 Perceived Usefulness (PU)

PU refers to the person's subjective belief that the technology will help them carry out their job in a better way (Davis, 1986). It is an important construct that results in individuals ultimately adopting or rejecting a technology (ibid). Rose *et al.* (2016) determine that PU is important for farmers: if the technology does not provide tangible benefits, it is not likely to be adopted. The construct was developed by Davis (1986) for TAM, using the work of Schultz and Slevin (1975) and Robey (1979). Schultz and Slevin

(1975) developed a 67-item questionnaire to understand system usage in the workplace. They discovered that seven dimensions were influential but that the impact the system had on the manager's job had the strongest correlation with behavioural intention to use. Robey (1979) built on this further and hypothesised that if a system did not help an individual in their job, they were unlikely to have a positive perception towards it. Davis (1989) used these studies outlined and others such as the self-efficacy theory, diffusion of innovations and behavioural decision theory to develop an appropriate scale for PU. The construct influences the attitude towards using the system and is three times more influential than perceived ease of use (Davis, 1989). If a person believes that the technology will improve their performance, they are somewhat willing to cope with a degree of difficulty in terms of using it. Furthermore, PU has a direct effect on the behavioural intention to use a system (Davis *et al.*, 1989).

Adrian *et al.* (2005) determines that the usefulness of SFT relates to increased productivity, lower production costs, reduced workload and faster task turnaround. Similarly, Thompson *et al.* (2018) cite cost saving, improvement in yield and convenience as the main drivers of adoption of PAT. Caffaro and Cavallo (2019) explain that the key benefits of SFT are improved yield and cost reduction. It is important to acknowledge that the farmer's perceptions of PU are heterogenous and will depend on the farm type, the technology in question, alongside the farmer's needs and perceptions (Kernecker *et al.*, 2019; Thompson *et al.*, 2018). However, these authors suggest that increasing productivity and improving work processes are of vital importance with environmental benefits not as significant. This is consistent with findings from Giua *et al.* (2022).

2.8.3 Perceived Ease of Use (PEOU)

PEOU is the degree to which the individual believes that using the technology is without effort (Davis, 1989). Gefen and Straub (2000) outline how it relates to the intrinsic characteristics of a technology. The construct was also developed by Davis (1986) for TAM, using the work of Schultz and Slevin (1975) and Robey (1979). Venkatesh and Davis (1996) outline how the PEOU construct is similar to self-efficacy beliefs and the judgements that individuals possess regarding whether they can carry out an activity or behaviour. Saadé and Kira (2007) explain that if a technology is easy to use, the user then perceives their self-efficacy as being greater.

PEOU has a direct causal influence on PU, as Davis (1986) outlines that a system which is deemed easy to use will result in increased usefulness for the user. For example, if the user saves time using a system due to its ease of use, it allows them to work smarter and thus is deemed useful (Davis *et al.*, 1989). PEOU also has a significant effect on attitude towards using the technology through the dimensions of self-efficacy and instrumentality (Davis *et al.*, 1989). If the user believes the technology is easy to use, the greater their sense of self-efficacy and reward will be.

Davis (1989) determine that PEOU is represented by the individual's perception of the technology being easy to use, easy to learn, easy for the user to become skillful at and their interactions with the technology would be clear. Gefen and Straub (2000) built on this further and state PEOU relates to ease of using the technology, ease of learning, flexibility and the clarity of the technology's interface. The authors argue that PEOU is particularly important when the ease of navigating the technology and using it directly relate to the outcome for which the technology is being used.

Farmers want a solution that works efficiently and is easy to use, providing information in a quick and user-friendly manner (Rose *et al.*, 2016). They are, however, often dissuaded from using SFT due to the perceived complexity of use (Bellon Maurel and Huyghe, 2017). McCaig *et al.* (2023) outlines that often farmers feel that a certain level of technical proficiency is needed to operate SFT and therefore specialised skills are needed. However, lack of time to upskill was cited as a key barrier to adoption (ibid). This suggests that the PEOU concept is important in the context of SFT. Furthermore, McCaig *et al.* (2023) discusses how farmers want more simplicity with SFT and therefore less reliance on vendors for support issues. Das *et al.* (2019) explains how farmers, in their study of Irish farmers views on SFT, perceived the technologies as being complex to use, particularly those who are non-adopters. Ultimately, Ronaghi and Forouharfar (2020) find that the farmer's perception about the ease of use of Internet of Things (IoT) impacts their intention to adopt.

2.8.4 Attitude

As outlined, attitude towards using a technology affects its adoption (Adrian *et al.*, 2005; Cochrane, 1993; Davis, 1989; Orr *et al.*, 2001). Attitude is a "*psychological tendency that is expressed by evaluating a particular entity or behaviour with some degree of favour or disfavour*" (Eagly and Chaiken, 1993, p. 1). Fishbein and Ajzen (1975) determine that attitude refers to a person's evaluation of a certain behaviour. Thus, attitudes are formed using attribute dimensions such as "good–bad, harmful–beneficial, pleasant–unpleasant and likeable–dislikeable" (Ajzen, 2001, p. 28). Mathieson (1991) reinforces that an attitude is formed towards a specific behaviour rather than a technology.

Attitudes develop when an individual forms beliefs regarding the object of the attitude, its attributes, and what the outcome of the associated behaviour will be (Ajzen, 1991). Consequently, attitude is one of the most influential factors on the farmer's behaviour (Terano *et al.*, 2015). Rose *et al.* (2018a) outline how attitude is influenced by the farmer's own beliefs and values. As a result, the farmer's intention to adopt a technology is directly related to their attitude and anticipation of its impact in economic benefit, farm performance and usefulness terms (Naspetti *et al.*, 2017; Rogers, 2003). A better understanding of attitudinal drivers could help to identify farmers who are more likely to adopt technology, resulting in them being targeted more efficiently (Konrad *et al.*, 2019).

The original TAM developed by Davis (1986) included attitude as a key construct and outlined how it is determined by PU and PEOU and subsequently leads to BI. However, Davis *et al.* (1989) removed it from the final model due to the weak relationship between PU and attitude and because of the partial mediation of beliefs on BI by attitude (Venkatesh, 2000). The newer model instead outlined that PU and PEOU had a direct influence on BI (Davis *et al.*, 1989). The authors determined that this created a more parsimonious, causal model (Venkatesh and Davis, 1996; Yousafzai *et al.*, 2007a). Conversely, the influence that attitude has on technology adoption is complicated and inconclusive (López-Bonilla and López-Bonilla, 2017; Teo, 2009; Ursavaş, 2012). Brown *et al.* (2002) indicate that attitude is a neglected construct in Information Systems research. Supporting this, Kim *et al.* (2009) criticise the revised TAM and extended versions of TAM for underestimating the importance of attitude. They conducted an analysis of studies examining the role that attitude has on BI and found that its effect is variable, according to the user's experience with the technology. Dwivedi *et al.* (2017) suggest that including attitude in models of technology adoption is worthwhile.

In an agricultural context, Mohr and Kühl (2021) and Shang *et al.* (2021) deduce that attitude towards using the technology influences the intention to use AI and digital farming solutions. However, Naspetti *et al.* (2017) observe that attitude does not a have significant effect on farmers' intentions to accept innovative production strategies. Further research concludes that attitude fully mediates the relationship between PU, PEOU and BI (Chen *et al.*, 2002; Chuang *et al.*, 2016; Mailizar *et al.*, 2021; Shih, 2004).

Other studies however determine that attitude has a partial mediating effect on BI (Agarwal and Prasad, 1999; Moon and Kim, 2001) or no mediating effect (Riemenschneider *et al.*, 2003). This discourse in the literature warrants further examination of the role of attitude on farmers' intentions to adopt SFT and its relationship with other variables.

2.8.5 Variables external to TAM

Variables external to TAM are antecedents to both PU and PEOU which help to explain the factors which impact both constructs and thus need considerable attention (Venkatesh and Davis, 1996). Taylor and Todd (1995) deduce that examples of antecedents to PU and PEOU could include characteristics of the decision-maker as well as the characteristics of the technology. Similarly, Baleghi-Zadeh and Mohd Ayub (2019) divide these external variables into four categories: individual influences, social influence, characteristics of the technology or system and facilitating conditions. TAM has been criticised for not examining these antecedents in greater detail (Venkatesh *et al.*, 2007). Indeed, Bagozzi (2007a) states that the shortcomings of TAM relate to identifying the antecedent determinants and the lack of examination of the impact of social and cultural factors on decision-making. Thus, individual influences such as personality, age, gender, trust as well as social influence could impact the farmer's perception of the usefulness of the technology and its usability and call for further investigation. This is discussed in greater detail in Sections 2.8.5.1-2.8.5.6.

2.8.5.1 Social influence

Assessing the effect of social influence (SI) or subjective norms (SN) in the TA literature is important, as recognised by several models such as the TPB, TRA, TAM2 and UTAUT (Graf-Vlachy *et al.*, 2018; Olschewski *et al.*, 2013; Vannoy and Palvia, 2010). However, many studies that adopt a behavioural approach to understand behavioural intention fail to determine the effect of social influence (Burton, 2004). Often this can be attributed to the complex nature of the impact of SI on technology adoption, thus the need for more research in this domain (Eckhardt *et al.*, 2010; Graf-Vlachy *et al.*, 2018; Legris *et al.*, 2003; Vannoy and Palvia, 2010; Venkatesh *et al.*, 2003). Social influence is defined as a person's belief that people close to them think that they should carry out a particular act (Ajzen and Fishbein, 1980). It is also represented by the subjective norm (SN) concept and is an important variable in several behavioural models (Ajzen, 1991; Fishbein and Ajzen, 1975; Venkatesh and Morris, 2000; Venkatesh *et al.*, 2003). The SN was reformulated as social influence in the Unified Theory of Acceptance and Use of Technology (UTAUT) and is defined as "*the degree to which an individual perceives that important others believe he or she should use the new system*" (Venkatesh *et al.*, 2003, p. 451). As such, the SN and social influence construct differ slightly in their descriptions, but Venkatesh *et al.* (2003, p. 451) state that while they are different "*each of these constructs contains the explicit or implicit notion that the individual's behavior is influenced by the way in which they believe others will view them as a result of having used the technology*". Furthermore, Eckhardt *et al.* (2010) suggest that SI is important for technologies that provide a utilitarian rather than hedonic benefit, of which it is argued that SFT provide. Sun and Zhang (2006, p. 622) define a system or technology as utilitarian when "*it is aimed mainly at outcome-oriented tasks*".

The original TAM did not find support for the inclusion of SN or SI as a construct. This was due to the difficultly in separating the direct effects of SN on BI, the indirect effect SN has on BI via attitude, and the difficulty in measuring the validity and reliability of the SN construct (Davis *et al.*, 1989). Accordingly, the authors acknowledge the need for further research. As a consequence, TAM is often criticised for failing to account for SI (Chen *et al.*, 2002). Certainly, Bagozzi (2007a), Eckhardt *et al.* (2010) and Zeal *et al.* (2010) highlight that the discrepancy in understanding the impact of social influence or the SN on behaviour may be due to how it is conceptualised. Social influence can be described as a cognitive process (Agarwal and Prasad, 1999), consisting of three distinct processes or forms: compliance, identification and internalisation (Kelman, 1958). These three processes are consistent with the Deutsch and Gerard (1955) characterisation of social influence as being normative, informational and value expressive. Compliance or normative social influence is recognised as the pressure to fit in with the norm and receive a favourable reaction from another person or group (Venkatesh and Bala, 2008). Identification or value-expressive influence is the adoption of a behaviour to maintain a satisfying relationship with another group or person (ibid). Internalisation or informational influence occurs when the individual is influenced because the behaviour matches their own internal belief and value systems (Venkatesh and Davis, 2000). With internalisation, a user perceives that information received from a credible source as enhancing their own knowledge (Lu *et al.*, 2005). Lord *et al.* (2001) outlines how this is particularly important if the user perceives themselves as having a lower level of confidence or knowledge. Eckhardt *et al.* (2010) highlight that a collective measurement of social influence is not adequate enough to ascertain its significance. Several studies have therefore introduced individualised measurements of social influence to include specific groups of people such as friends, households, and peers (Hu *et al.*, 2003; Yang *et al.,* 2007). Taylor and Todd (1995) use peer influence and superior influence in understanding the influence of the SN on behavioural intention. Shen *et al.* (2006) examine the influence of SI on online learning programs. They divide SI into instructor, mentor, and peer influence. Therefore, individualised measures of SI will be adopted in this study, consistent with Yang *et al.* (2007), Hu *et al.* (2003) and Taylor and Todd (1995), as will a collective measure of SI used by Venkatesh *et al*., (2003).

In an agricultural context, social influence and interactions influence the adoption of innovations (Kernecker *et al.*, 2021; Klerkx *et al.*, 2012). Jayashankar *et al.* (2018) however deduce that the role that the farmer's network plays in facilitating technology adoption requires further examination. Networks are identified as crucial in technology adoption, diffusion and innovation decisions (Rampersad *et al.*, 2012), transferring knowledge within and between organisations (Marchiori and Franco, 2020; Massaro *et al.*, 2017). Typical sense-making tasks regarding technology adoption include a cost-benefit analysis regarding the effort and time associated with adoption (Abbas *et al.*, 2018). Gibbs *et al.* (2007) acknowledge that in small businesses, technology adoption is likely to be influenced considerably by the business network. Equally, SMEs rely significantly on their business networks for information on new technologies (Windrum and Barranger, 2002). Specifically, new knowledge from actors outside the firm is important in developing a competitive advantage (Inkpen and Tsang, 2005). Such knowledge can be shared through education and training, communication materials, events and sustained interaction with network members (Butler *et al.*, 2007). However, trust between actors is a critical factor not only in the development of business network relationships but also during knowledge transfer and the willingness to share information (Inkpen and Tsang, 2005; Massaro *et al.*, 2017). If the actors trust each other, there is more likely to be more open communication and information sharing (Seppänen *et al.*, 2007).

Farmers participate in interlinked networks composed of human and non-human entities (Gray and Gibson, 2013) such as peer farmers, farm advisors, associations, cooperatives, material providers, vendors, agribusinesses, artifacts and organisational structures (Jallow *et al.*, 2017; Joffre *et al.*, 2019; Klerkx, 2021). Participation in such networks supports their innovation behaviours (Klerkx *et al.*, 2010). Although the network consists of multiple actors, the principle of homophily is evident with farmers mostly connecting with other farmers who they see as similar (Phillips *et al.*, 2021). Homophily describes the concept that people are more likely to develop relationships with those who share similar attitudes, values and opinions (Kossinets and Watts, 2009). It is intensified by proximity, meaning that if actors are geographically or physically close to each other, they are more likely to form a relationship (McPherson *et al.*, 2001). Limited interaction with actors in the network, besides from other farmers, can further limit the innovation potential of the farm (Knierim *et al.*, 2019). The main actors in the farmer's network and their corresponding influence on the farmer are discussed in more detail below.

2.8.5.1.1 Farmer Groups

Membership of a farmer group such as a farmers' association, a cooperative or a farming collective can influence the decision to adopt technology (Jallow *et al.*, 2017). Farming cooperatives are commonplace in the EU and can be an effective means of reducing the cost associated with purchasing new technologies (Bijman and Iliopoulos, 2014). A farmer cooperative is an economic organisation where farmers that produce similar produce pool resources and share costs (Wang *et al.*, 2019). Information passed among the farmer members of the cooperative can help reduce the uncertainty around technology adoption and help to disseminate the benefits of adoption (Barnes *et al.*, 2019b). However, if the cooperative determines that adopting a technology will require effort in terms of time and resources, it decreases the likelihood of adopting the innovation or technology (Wang *et al.*, 2019). Membership of the cooperative will also have an impact of the type of technology adopted, as members are more likely to adopt the technology that has been used by other members (Barnes *et al.*, 2019a). However, Martínez-García *et al.* (2015) conclude from their study of technology adoption among dairy smallholders, that membership of a cooperative was not important in terms of the adoption of new technologies, but did lead to more successful implementation.

Farmers who are a member of a farming cluster, which is characterised as a formal farming group working together to reduce costs and increase access to market, have a positive relationship with technology adoption (Joffre *et al.*, 2020). Farmer clusters tend to be a simplified form of a farmer cooperative in that there are limited legal and financial obligations and limited liability as such (Ha *et al.*, 2013).

2.8.5.1.2 Farm Household

In the EU, over 95 per cent of farms are classified as a family farms (Eurostat, 2019) thus decisions are often made across generations or as a household (Glover, 2013; Martin-Clouaire, 2017). The farming family is recognised as a central decision-maker in European agriculture, but it is however highly heterogeneous depending on various contexts (Huber *et al.*, 2018). Thus, understanding the farm household or family's influence on the decision to adopt SFT is important. The role of the family household is particularly important for smaller farms where family labour is essential to the farm's survival (Cush and Macken-Walsh, 2016). These family members are recognised as having a key influence on farmers' adoption of ICT, through sharing information, particularly for those who are less technologically aware (Warren, 2004). Martínez-García *et al.* (2015) concurs with this by identifying farm family members as a key source of information with regard to technology adoption. They are, however, not as influential as other members such as veterinarians or farm advisors (ibid). Similarly, Blasch *et al.* (2022) highlights that information from family members is the second most relevant source of information after farm advisors.

2.8.5.1.3 Farm Advisors/Extension Agents

Farm advisors, agronomists and extension agents play an important role in diffusing information and advice on SFT to farmers (Eastwood *et al.*, 2017b; Jakku and Thornburn, 2010). Equally, negative information on technologies received from advisors or farmers can significantly influence the farmer's adoption decision (Pivoto *et al.*, 2019). Ayre *et al.* (2019) outlines how advisors can play a broker or intermediate role between farmers and new information, knowledge, and new technologies. These advisors support farmers with their decision-making on several levels; economic, technical, organisational, and social (Dockès *et al.*, 2018). Knierim *et al.* (2018) suggest that information from farm advisors, which are deemed independent from any company, as the most influential source of information. Not only do advisors provide information, they can also help farmers to make sense of the data collected from many farm systems and technologies (Jakku and Thornburn, 2010; Klerkx and Proctor, 2013). Furthermore, they help to reduce the level of uncertainty that farmers feel regarding SFT implementation (Higgins and Bryant, 2020) and thus play a 'sense maker' role (Eastwood *et al.*, 2019). Accordingly, farm advisors are a significant influence on the intention to adopt SFT. However, with the advent of digital technologies, the relationship between the farm advisor and the farmer has changed with less physical interaction as a result (Eastwood *et al.*, 2018). Indeed, many farm advisors struggle with constantly changing technologies and the associated data analysis required (Nettle *et al.*, 2018; Prager *et al.*, 2016) diversifying their role considerably (Ayre *et al.*, 2019).

2.8.5.1.4 Peer farmers

Knierim *et al.* (2018) outline how interactions between farmers can influence the adoption of SFT. Blasch *et al.* (2022) find support for this, citing peer farmers as one of the most influential sources of SFT information. Certainly, farmers who become aware of SFT through other farmers are significantly more likely to adopt the technology, due to the ability to observe the technology in practice, resulting in a greater understanding of the features and benefits involved (Blasch *et al.*, 2022). Furthermore, Pathak *et al.* (2019) and Öhlmér *et al.* (1998) posit that the farmer's personal network is very important in helping to check the farmer's choice and to find options for assessment. This is supported by Pannell *et al.* (2006) who find that in the early stages of the adoption decision, the farmers' peer network can help to reduce the uncertainty around the technology. However, Barnes *et al.* (2019b) question the role of peer farmers in aiding SFT adoption, due to the sophisticated technical nature of the technologies.

Table 2.2 outlines some of the key studies that have included SI as a construct when using TAM.

Table 2.2 Recent studies integrating social influence and TAM

Authors & year	Context	Methodology	Findings	Further Research
Vanduhe *et al.* (2020)	Gamification platform for education training.	Questionnaire to full time instructors lecturing with 375 responses.	• SI influence on PU. • SI has no influence on PEOU.	Future studies extend to different sectors and universities to improve the generalisability.
Zhang *et al.* (2020)	Automated vehicle acceptance.	Questionnaire of drivers with 647 responses.	• SI has a direct effect on PU. • SI has a direct effect on BI. • SI influences PEOU.	Longitudinal study recommended.
Patel and Patel (2018)	Consumer adoption of internet banking.	Questionnaire with 284 responses.	• SI influence on BI (relationship between SI and PEOU or SI and PU not tested)	Extend research to new locations and compare with existing results.
Wang *et al.* (2017)	Teachers using the cloud/	Questionnaire with 34	• SI influences PU.	Larger scale study and

Authors & year	Context	Methodology	Findings	Further Research
	platform for online collaboration.	responses from teachers working at university.		longitudinal study.
Wu and Chen (2017)	Use of Massive Open Online Courses (MOOCs).	Questionnaire with 252 participants.	• SI has a positive effect on PU. • SI does not have an effect on attitude.	Longitudinal study recommended.
Nabhani *et al.* (2016)	Mobile broadband adoption by farmers.	Questionnaire with 191 responses.	• SI influences PU. • SI has no significant influence on PEOU.	Future research in different sub-sectors of agriculture will broaden the research perspectives.
Dutot (2015)	Near Field communication adoption.	Questionnaire to business school students, members of professional groups with 320 responses.	• SI has and influence on PU). • SI has no influence on PEOU.	Extend the research to other markets worldwide.
Wang and Chou (2014)	Online Group-Buying Repurchasing Intention.	Questionnaire with 1163 responses.	• SN influences PU.	Extend the research to different countries and include a measurement of trust.
Kulviwat *et al.* (2009)	High tech innovations (personal digital assistant).	Questionnaire with 260 responses.	• SI influences BI • Attitude toward adoption mediates the effect of SI on BI.	Examine the role of social influence in the context of a full technology acceptance model. Examine the role of individual characteristics.

The table outlines that when integrating SI with TAM, one of the most tested relationships is between SI and PU. This suggests that if farmers think that important people in their network believe that they should use SFT, they are more likely to perceive the technology as useful. Intrinsically, positive information regarding the effectiveness of SFT from the network influences the farmer’s overall perception of PU. An alternative approach to determining the importance of the farmer’s network in diffusing information and encouraging technology adoption could be assessed using Actor Network Theory (ANT) (Oreszczyn *et al.*, 2010). Undoubtedly, ANT offers a very useful framework for understanding complex networks of actors in an organisational context and their influence on technology adoption. However, given that the main objective of this study is not exclusively centred on examining the influence of the network on adoption, but instead understanding the impact of key internal and external factors on intention to adopt, integrating SI with TAM is deemed more suitable.

2.8.5.2 Personality Traits

Individuals adopt technology at different rates, while some reject technologies completely due to differences in their personality (Agarwal and Prasad, 1998; Lu *et al.*, 2005; Turan *et al.,* 2015). Personality traits are key indicators of how a person deals with situations within their environment (Ali, 2019) and their relationship with, and use of, technology (Svendsen *et al.*, 2013). Certainly, Venkatesh (2021) determines that individual characteristics such as personality are critical aspects to investigate when determining technology adoption. Mothersbaugh *et al.* (2020) explain that many theories of personality exist, but those which focus on personality traits are the most useful when understanding marketing or consumer psychology. Certainly, the personality of an entrepreneur or businessperson impacts the adoption of innovation within SMEs (Marcati *et al.*, 2008).

Personality traits are recognised as antecedent variables to the farmer's behaviour (O'Leary *et al.*, 2018; Willock *et al.*, 1999). Thus, understanding how the farmer's personality traits influence technology adoption can lead to better explanation of intention (Alvarez and Nuthall, 2006). However, Rose *et al.* (2018c), Bukchin and Kerret (2018) and Ali *et al.* (2017) note a research gap in determining how farmer personality traits impact behaviour. The challenge that researchers face when integrating personality with the IS literature, is the range of potential personality variables or traits that are available (Devaraj *et al.*, 2008). For example, the five-factor model from Costa and McCrae (1992) measures personality using five traits: neuroticism, openness, extraversion, agreeableness, and conscientiousness. However, innovativeness as a personality trait, reflecting an individual's willingness to change, is seen as particularly influential (Hurt *et al.*, 1977). Individuals might have similar perceptions of the usefulness and ease of use of a technology, but a person with a higher level of innovativeness might have a higher intention to adopt (Fagan *et al.*, 2012). Consequently, researchers in marketing and business domains have recognised the importance of measuring innovativeness in innovation adoption related studies (Aldahdouh *et al.*, 2020). Understanding the innovativeness of a person is important in determining its relationship with other variables in technology adoption models and to understand when individuals are likely to adopt an innovation, helping the process of diffusion (Goldsmith and Foxall, 2003). Furthermore, it facilitates an understanding of people in the social system who can act as change agents and encourage others in the network to adopt the technology (Rogers, 2003).

There are three approaches to conceptualising and measuring innovativeness; behavioural, global and domain-specific (Goldsmith and Foxall, 2003). Behavioural focuses on the activity of adoption and whether the person is an adopter or non-adopter. In the Diffusion of Innovation Theory (DoI) Rogers (1962), outlines how different categories of adopters exist: innovators, early adopters, early majority, late majority, and laggards. These categories ultimately measure the innovativeness of an individual compared to others in society. Although recognised as influential, Midgley and Dowling (1978) and Goldsmith and Hofacker (1991) criticised the behavioural characterisation of innovativeness, arguing that its conceptualisation was not sufficiently abstract. Furthermore, the DoI theory allows researchers to explain adoption but does not help with predicting adoption (MacVaugh and Schiavone, 2010). Innovativeness as a global personality trait categorises people according to their reactions to new and different concepts and situations (Goldsmith and Hofacker, 1991). Finally, domain-specific innovativeness relates to the concept of innovativeness to a particular domain of interest – for example, fashion or movies. Goldsmith and Hofacker (1991) argued that it is more important to understand a person's innovativeness within a specific domain or product category as opposed to their overall innovativeness. Based on this, Agarwal and Prasad (1999) developed the concept further and introduced a new construct to illustrate how psychometric properties influence both technology acceptance and adoption. This construct known as personal innovativeness in the domain of information technology (PIIT) is described as "*the willingness of an individual to try out any new information technology*." (p. 206). PIIT shapes an individual's perceptions regarding a particular technology (Dabholkar and Bagozzi, 2002) and is important in explaining an individual's adoption and acceptance of technology (Abubakre *et al.*, 2020; Dai *et al.*, 2015). Furthermore, Lu (2014) determines that PIIT as a personality trait impacts human behaviour on a long-term basis. However, Rosen (2004) outline that PIIT has not been integrated in sufficient studies examining technology acceptance. Therefore, understanding the role that PIIT plays on technology adoption is critical (Fagan *et al.*, 2012).

Agarwal and Prasad (1998) deduce that including variables related to the individual, such as PIIT, could include the predictive power of models like TAM. They deduce that there is a significant relationship between PIIT and PU and PIIT and PEOU. However, the relationships between PIIT and the constructs in TAM are varied. Some studies demonstrate that PIIT is a direct antecedent to intention (Lu *et al.*, 2005), while others show that it has a moderating effect on BI (Yi *et al.*, 2006b). In their original study, Agarwal and Prasad (1998) did not find support for PIIT directly influencing BI or moderating the relationship between PU, PEOU and usage intention. Ciftci *et al.* (2021) explain that the differences in results can be explained by differences in the type of technology examined, the demographic of study and the culture. The relationships between PIIT and the constructs in TAM are examined in greater detail in Section 3.3.1.1.

Many studies examining the impact of personality traits on TA also use the Technology Readiness Index (TRI) from Parasuraman (2000). He defines technology readiness as "*people's propensity to embrace and use new technologies for accomplishing goals at home and work*" (Parasuraman, 2000, p. 308). As such, the TRI measures readiness to accept new technologies and suggests that four beliefs or feelings impact technology adoption; optimism and innovativeness which are seen as "contributors", while discomfort and insecurity are defined as "inhibitors". The TRI and PIIT measure a similar construct of people's willingness to adopt new technologies. However, they differ considerably in their operationalisation. TRI is developed through a 36-item scale (Parasuraman, 2000) or a 16-item scale for TRI 2.0, as developed by Parasuraman and Colby (2014). Blut and Wang (2019) posit that using the full TRI instrument in surveys is very long and therefore not always convenient to use. The PIIT construct is measured by a 4-item scale, focused only on innovativeness. Thus, as this study is concerned with innovativeness as a personality trait, the PIIT construct is deemed more suitable. Furthermore, as this study is not solely focused on the role of innovativeness but addresses the key influences on SFT adoption, the use of PIIT is reasoned to be more appropriate.

Self-efficacy could also have been used as an alternative construct to PIIT. Self-efficacy relates to an individual's beliefs regarding their competency in a particular domain, leading to a successful outcome (Bandura, 1997). It focuses on a person's perceptions of what they can do with the skills they have (ibid). Compeau and Higgins (1995) developed this concept further, introducing computer self-efficacy which corresponds to a person's judgment of their ability to use a computer. Self-efficacy is recognised as being one antecedent to the perceived ease of use construct in the TAM (Venkatesh and Davis, 1996). However, PIIT addresses a person's willingness or risk-taking tendency to try out new technologies in a broader sense rather than the belief that they have the competency or ability to use the new technology. PIIT helps to demonstrate how perceptions towards technology are formed and how this influences the intention to adopt a technology (Agarwal and Prasad, 1999). The construct can be used to identify those individuals who are likely to adopt a technology before the critical mass. Identifying such people and using them as change agents to further encourage adoption among a mass audience can facilitate effective diffusion (López-Bonilla and López-Bonilla, 2012).

2.8.5.3 Trust & Trusting beliefs

Several studies have integrated trust with TAM when focusing on new technologies such as online shopping (Gefen *et al.*, 2003), electronic logistics information systems (Tung *et al.*, 2008), e-government services adoption (Belanche *et al.*, 2012), location sharing applications (Beldad and Kusumadewi, 2015) and fitness applications (Beldad and Hegner, 2017). Consequently, Belanche *et al.* (2012) recommend integrating trust as a construct within TAM for technologies where uncertainty is high. For example, Tung *et al.* (2008) demonstrate that incorporating trust and perceived financial cost into TAM increased its explanatory capacity when determining e-logistics adoption. Table 2.3 outlines the findings from recent studies integrating trust with TAM.

Table 2.3 Studies integrating trust with TAM

Authors and year	Context	Methodology	Key Findings	Future Research
Choung *et al.* (2022)	Artificial Intelligence technologies.	Quantitative - survey of 312 college students.	• Trust shapes people's attitudes and • acceptance of AI technologies • Trust influences PU.	Extend the research to the adoption of AI in more high-risk situations. Develop different measures of trust for initial and continued trust.
Saleh *et al.* (2022)	E-Learning systems.	Quantitative - survey of 367	• Trust influences PU.	Examine gender differences.

Authors and year	Context	Methodology	Key Findings	Future Research
		teachers and college students.	• Trust influences PEOU.	Extend to other countries.
Shrestha *et al.* (2021)	Blockchain Technology - Shopping Cart System (SCS) and Data Sharing System (DSS) (B2C).	Quantitative - survey of 63 for SCS and 50 for DSS, recruited online and through a university.	• Trust positively affects users' attitudes. • (Relationship with PU/PEOU not tested).	Consider the role of participants' background on their behavioural intention to use blockchain technology.
Dhagarra *et al.* (2020)	Technology in healthcare service delivery (B2C).	Quantitative - survey of 416 patients and accompanying members.	• Trust is positively associated with PU. • Trust is positively associated with Behavioural Intention (BI).	Methodological improvements considering fixed and random effects.
Kamal *et al.* (2020)	Telemedicine Services (B2C).	Quantitative survey of 226 patients.	• Trust positively influences the Behavioural Intention to use. • (Relationship with PU/PEOU not tested).	Use a sample more representative of the general population. Examine psychological determinants of acceptance.
Herzallah and Mukhtar (2016)	e-Commerce Services in Small and Medium-Sized Enterprises (B2B).	Quantitative - survey of 250 managers of SMEs	• PEOU influences trust. • Trust influences Behavioural Intention.	Apply the research to additional technology domains.
Belanche *et al.* (2015)	E-government services (B2C).	Quantitative - survey of 416 potential users.	• PEOU positively affects trust. • Trust positively affects PU. • Trust positively affects attitude towards use. • Trust positively affects the intention to use.	Longitudinal study to measure influence of trust on actual adoption. Extension of context to other technology to confirm the partial mediation role of trust.

Authors and year	Context	Methodology	Key Findings	Future Research
Zimmer *et al.* (2010)	Online information disclosure (B2C)	Quantitative - survey of 264 students.	• Trust in the website has a positive influence on attitude to disclose information.	Inclusion of familiarity, to understand if trust already exists.
Tung *et al.* (2008)	Electronic logistics information system in healthcare (B2B).	Quantitative - survey of 258 nurses.	• PEOU has a positive effect on trust. • Trust has a positive effect on PU. • Trust has a positive effect on BI.	Extend to different IT contexts in the medical industry.
Benbasat and Wang (2005)	Online product recommendation agents (B2C).	Laboratory experiment.	• Trust directly influences users' intention to adopt the technology and indirectly through PU. • Impact of PEOU on intention to adopt agents is mediated by PU and trust.	Examine if the conceptualisation of trust should include other relevant beliefs.
Wu and Chen (2005)	Online Tax (B2C).	Quantitative - survey of 1032 online tax users.	• PEOU influences Trust. • Trust influences PU. • Trust positively influences Attitude.	Additional research with an alternative conceptualisation of trust.
Yu *et al.* (2005)	T-Commerce (Television Commerce) (B2C).	Quantitative – survey of 947 experienced users and 115 inexperienced users.	• Trust has a positive influence on the attitude towards using T-Commerce. • Trust has a significant positive impact	Longitudinal study to examine the factors that influence consumers' adoption of t-commerce in the home environment.

Authors and year	Context	Methodology	Key Findings	Future Research
			on Behavioural Intention to use the technology. • (Relationship between Trust and PU/PEOU not examined)	
Gefen (2004)	Enterprise resource planning (ERP) customisation vendor (B2B).	Quantitative - survey of 133 clients working in manufacturing companies.	• Trust increases the PU of the ERP technology.	Longitudinal study to investigate causation.
Gefen *et al.* (2003)	Online Shopping (B2C).	Quantitative – survey of 72 students.	• PEOU has a significant influence on trust. • Trust has a significant influence on PU. • Trust has a direct influence on intended use.	Examine the influence of the user's level of experience. Longitudinal study to examine how antecedents and relationships of trust change over time. Assess if the conceptualisation of trust in e-commerce can be extended.
Pavlou (2003)	e-Commerce (B2C).	Exploratory study - 103 students. Second, confirmatory study - 155 online consumers.	• Trust is positively related to PEOU. • Trust is positively related to PU. • Trust is positively associated with BI.	Identify additional factors that influence consumers' adoption of e-commerce.
Suh and Han (2002)	Internet Banking (B2C).	Quantitative survey of 845 users from 5 major banks.	• PU has a positive impact on trust. • Trust has a positive impact on the Attitude	Applying the research to other technology domains. Consider examining other

Authors and year	Context	Methodology	Key Findings	Future Research
			towards using Internet Banking. • Trust has a significant positive impact on Behavioural Intention.	beliefs and the precedents of trust.

In summary, the studies, outlined in Table 2.3, explain the relationships between the variables within TAM when integrating trust. It merits attention that not all the studies integrated all elements of TAM when testing the relationship with trust. Furthermore, many of the studies examine the role of trust in B2C transactions. However, the main implications that can be derived are that PEOU acts as an antecedent to trust, while this trust drives PU. Furthermore, trust has a positive influence on attitude.

2.8.5.3.1 Defining Trust

Integrating trust with TAM is complicated due to differences in how researchers conceptualise and define the construct (Benamati *et al.*, 2010). These difficulties relate to trust being an abstract and multidimensional concept (Bhattacherjee, 2002; Li and Betts, 2003; Wang and Emurian, 2005). It is interdisciplinary and can be viewed differently according to the discipline examining the construct (Li and Betts, 2003; van Zeeland-van der Holst and Henseler, 2018). For example, disciplines such as economics, psychology, philosophy, marketing and management all conceptualise the construct differently (Wang and Emurian, 2005). While van Zeeland-van der Holst and Henseler (2018) indicate that trust in the industrial marketing domain can be viewed from five different perspectives: economic, cognitive, behavioural, psycho-economical, and psycho-sociological.

Hupcey *et al.* (2001) explain that in the psychology domain, trust is most commonly conceptualised as being an expectancy that another person can be relied upon. It is seen as being a general disposition to trust and therefore a cognitive process (Evans and Krueger, 2009). However, Lewicki and Bunker (1995) criticise the psychological view of trust by determining that trust cannot be seen as a personal trait and instead should be viewed from an objective social reality. Within sociology, trust is examined from a societal perspective, focusing on how trust functions within societal norms and structures (Lewicki and Bunker, 1995). Lewis and Weigert (1985) further explain that trust is needed for successful social relationships. Trust, therefore, takes a social exchange perspective where it is continuously evolving, based on the outcome of social interactions, governed by the norms of fairness, reciprocity, and mutual benefit (Luo, 2005). This social exchange theory (SET) approach determines that trust is built based on continued, successful exchanges between various parties (Kelliher *et al.*, 2018; Lioukas and Reuer, 2015). Consequently, trust from a sociological and psychological perspective is a predictive process which relates to the trustor assessing the other party's reliability and therefore forecasts future behaviour (Doney and Cannon, 1997). However, McEvily and Tortoriello (2011) question the relevancy of trust measurements from a social perspective when examining the concept from an organisational point of view. Equally, individual and personal relationships are somewhat overlooked in the social perspective of trust (McKnight and Chervany, 2001).

Welch *et al.* (2005) explain that when sociologists define trust, they use words such as reciprocity, cooperation and moral obligation, whereas from an economic perspective, words such as commodity and resources are used more frequently. Thus, the economic perspective sees trust as arising from social capital, forming through networks and relationships within communities and, as such, trust facilitates economic progress (Putnam, 2000). Trust is generally seen as a calculative process where an individual calculates the cost or reward of staying in the relationship or leaving (Williamson, 1991). The cost and benefits of trusting or being vulnerable to the other party are considered (Hasel and Grover, 2017). A common criticism of this perspective of trust is the classification of buyers and sellers as rational beings, as well as difficulties in measurement (Furlong, 1996). Finally, trust from a marketing perspective has taken much of the social-psychological thinking (Raimondo, 2000), recognising that trust is important to successful relationship marketing (Morgan and Hunt, 1994).

McKnight and Chervany (2001) also categorise trust differently based on the domain under examination. They cite the discipline of psychology and economics as defining trust as dispositional, which describes the willingness to depend on others across a broad range of situations and types of people. This differs from interpersonal trust in that it relates to general situations rather than specific situations or people (McKnight *et al.*, 2004). Sociology views trust as institution-based trust (Bachmann and Inkpen, 2011). This stipulates that generally people can rely on, or trust in, others due to the structures that exist in society such as regulation, seniority and enforcement (Lewis and Weigert, 1985). Institution-based trust is conceptualised as consisting of structural assurance and situational normality (ibid). Structural assurances outline how a person believes that there are structures in place such as guarantees or contracts which enable trust (Pavlou and Gefen, 2004). Similarly, situational normality is assumed which refers to the belief that success is likely because the situation appears normal or favourable (ibid). Consequently, trust breaks down in abnormal situations.

Social psychology conceptualises trust as interpersonal, consisting of trusting beliefs (perceptual), trusting intentions (intentional) and trust-related behaviour (behavioural) (McKnight and Chervany, 2001). Trusting beliefs relate to a person's beliefs that the other person in the relationship has positive traits such as competency, benevolence and integrity that will ensure success (McKnight and Chervany, 2000). Trusting intention is described as a person's willingness to trust another party, even though negative consequences are possible (ibid). Trust-related behaviour includes activities such as sharing, co-operating, accepting influence, and transacting business (McKnight *et al.*, 2004). Thus, this definition of trust consists of a person's willingness to depend, and the subjective probability of depending also.

As previously outlined, trust can be characterised as being multi-faceted comprising cognitive, affective and behavioural dimensions (Lewis and Weigert, 1985; McAllister, 1995; Moorman *et al.*, 1992) and thus being a belief, attitude, intention and a behaviour (Gefen *et al.*, 2003). Cognitive trust is based on knowledge gathered through observation and reputation, alongside the trustor's (trusting party) prediction that the trustee (party to be trusted) will fulfil their obligations (Johnson and Grayson, 2005). McAllister (1995) thus argues that cognitive trust is centred around an individual's beliefs regarding dependency and competency of the other party. Affective trust leads on from cognitive trust and is based on the feelings and emotions that arise from the level of service and care received by the trustor from the service provider (McAllister, 1995). Behavioural trust follows on from both cognitive and affective trust, leading to specific actions (Lewis and Weigert, 1985).

2.8.5.3.2 The Researcher's Conceptualisation of Trust

Trust in this study is conceptualised using a social-psychological and marketing perspective. Consistent with this approach, trust is viewed as interpersonal trust comprising cognitive elements. Thus, trust is a "*set of specific beliefs in another party* *which include "integrity, benevolence and ability*" (Gefen *et al.*, 2003, p. 60). These beliefs, cited by Gefen, are based on the Integrative Model of Organizational Trust from Mayer *et al.* (1995). This model has been used in many prominent studies, examining trust in different disciplines including agribusiness, and is particularly useful when examining trust in a business setting (Scherer and Wimmer, 2014). Furthermore, this model was developed with the intention of being used across competing disciplines including management, psychology, sociology, philosophy, and economics (Schoorman *et al.*, 2007). The model relates to interpersonal trust which McAllister (1995) determines significantly enhances relationship quality, leading to better cooperation, communication, and satisfaction. It is argued that this is important in the adoption of new or sophisticated technologies.

Conversely, the model is criticised for being focused on an organisational setting and thus its contribution to understanding trust from a social perspective is narrow (Schoorman *et al.*, 2007). Hasel and Grover (2017) critique the model for overly relying on the cognitive aspect of trust and ignoring the affective element. Similarly, the model assumes rational thinking and overlooks the emotional aspects of trust (Santana and Cook, 2020). Furthermore, Burke *et al.* (2007) highlight a major weakness of the model in failing to specify the outcomes of trust. However, generally the seminal model has received praise for its applicability and is determined to be an influential model to examine trust (Fulmer and Gelfand, 2012; Hancock *et al.*, 2023; Schoorman *et al.*, 2007). As the model is focused on an organisational or workplace setting (Dirks and Ferrin, 2001), it is deemed suitable for this study which uses a B2B lens to understand the factors influencing farmers' intentions to adopt SFT.

The Integrative Model of Organizational Trust is based on trust between two parties: the trusting party (trustor) and the party to be trusted (trustee) in an organisational setting. Thus, in this study, the trustor is the farmer, and the trustee is the SFT vendor, as detailed further in Section 2.8.5.3.3. Trust is defined as a cognitive process, largely ignoring the affective element, and is characterised as "*the willingness of a party to be vulnerable to the actions of another party, based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party*" (Mayer *et al.*, 1995, p. 712). Furthermore, this model of trust integrates psychological and relational dimensions of trust between buyers and sellers (Mayer *et al.*, 1995). The authors determine that the antecedents or characteristics of trust are trustworthiness, namely the ability, benevolence, and integrity of the trustee, as well as the individual's propensity to trust. Ability refers to the person's perception that the organisation has the competency, skills, and knowledge to conduct the agreed behaviour. Ability is domain specific in that an individual may have ability in one domain but have little experience or knowhow in a different domain. Saleh *et al.* (2013) determine that ability relates to the salesperson's communication skills, providing products that are sufficient for purpose and being realistic with promises. Benevolence relates to the individual's perception that the organisation or individual is doing good beyond solely making a profit. For example, taking a proactive interest in the users' needs and concerns (Mayer *et al.*, 1995; Svare *et al.*, 2019). Integrity refers to the person's perception that the company or trustee will follow a set of principles or rules that are deemed fair and reasonable both during and after the exchange (Mayer *et al.*, 1995). Opportunism and benevolence are linked; if an organisation is seen as highly opportunistic, this translates to a low level of benevolence and vice versa (Svare *et al.*, 2019). Mayer *et al*. (1995) determine that these three dimensions of trustworthiness should be viewed along a continuum and as being related but separable. Schoorman *et al.* (2007) explains that these elements of trust are particularly important in buyer-seller relationships. The propensity to trust can be described as a willingness to trust in a specific situation (Mayer *et al*., 1995). It is unique to individuals based on their personality, experiences (Colquitt *et al.*, 2007) and culture (Hofstede *et al.*, 2010).

This study equally could have adopted a sociological perspective using social exchange theory (SET). SET is a broad sociological and psychological theory which explains that relationships involve a series of mutual transactions between individuals, based on commitment, reciprocity, flexibility and trust (Blau, 1964; Khalid and Ali, 2017). It has been used to examine trust in several organisational settings and between leaders and employees (Ahmad *et al.*, 2022; Anwar *et al.*, 2023; Cropanzano and Mitchell, 2016; Dutt *et al.*, 2022). However, major criticisms of SET, and why it was ruled out for this study, relate to its lack of theoretical foundations and its broadness (Cropanzano *et al.*, 2017). This is in part due to there being too many overlapping constructs to represent the elements of SET, namely a starting action, a relationship between parties, and a responding action (Cropanzano and Mitchell, 2016). Indeed, Mitchell *et al.* (2012) explain that SET is more a framework rather than a theory, with varying concepts and principles. Hadinejad *et al.* (2019) further question the generalisability of studies using SET.

An institutional-based approach to trust would also have been feasible for this study. However, such an approach is focused on the mechanisms in an organisation that facilitate trust, such as disciplinary measures, contracts, policies or structural assurances (Lewis and Weigert, 1985). McKnight and Chervany (2001) explain that trust is therefore seen as a belief relating to the favourable conditions and rules within an organisation that help to deliver success. Although it would be interesting to examine how trust in SFT vendors' certifications, licenses and guarantees impact the farmer's perceptions and intentions to adopt SFT, this research is more concerned with the relationship between the farmer and the SFT vendor, rather than the institutional structures in place. Indeed Shockley and Shepherd (2016) highlight that institutional-based trust can be problematic as who, or what the trustee is, is not always clear. Conversely, Dirks and Ferrin (2001) stipulate that personal engagement or connections helps to build a sense of reliability and assurance that is crucial for trust, as consistent with an interpersonal view of trust.

2.8.5.3.3 Trust in the SFT vendor

For this study, as outlined, trust is focused on the provider or developer of the technology, rather than the technology in question. This is consistent with several studies which demonstrate that trust in the technology provider is as important as trust in the technology (ad and Hegner, 2017; Wu *et al.*, 2014). Pavlou (2003) argues that if there is no trust in the developer or vendor of the technology, then the user is unlikely to have high levels of trust in the technology itself. Certainly, in the study of agri-IoT adoption from Jayashankar *et al.* (2018), trust is conceptualised as trust in the agricultural technology provider. Thus, as outlined, trust is conceptualised in this study using the Mayer *et al* (1995) Integrative Model of Organizational Trust, with the trustor being the farmer and the trustee the SFT vendor.

Trust antecedents are namely the ability, benevolence, and integrity of the SFT provider. Beldad and Kusumadewi (2015) conclude that the risk associated with using a specific technology increases the importance of trust as a predictor of technology adoption. One source of this risk is supplier uncertainty, as outlined by Meijer *et al.* (2007), which relates to the farmer's perception of the reliability of the supplier and whether they will keep to their agreements regarding service, quality and price. Eastwood and Renwick (2020) explain that farmers can often uninstall technology due to poor after-sales quality from the vendor. The adoption of SFT has thus been hampered by farmer hesitancy and scepticism regarding implementation (Newton *et al.*, 2020; Reichardt and Jürgens, 2009). This is consistent with Godoe and Johansen (2012) who deduce that feelings of insecurity or fear, and lack of trust about a specific technology and its provider, can hinder its adoption process. Fox *et al.* (2021) explains that trust in the vendor was an important factor in both the initial adoption decision and continued use of a technology for farmers. Rotz *et al.* (2019a) explain that farmers often distrust the calculations made by SFT, questioning the competency of the provider. Data is hugely important to the farmer to improve their decision making but the potential misuse of data from technology providers or vendors, and sale of data to third parties can lead to further scepticism and an aversion to SFT adoption (Jayashankar *et al.*, 2018). In addition, concerns over liability between vendors and the farmer has led to further reluctance to fully embrace SFT (Ofori and El-Gayar, 2020). Subsequently, issues such as ownership of data (Jakku *et al.*, 2019), balance of power between the farmer and the technology supplier (He *et al.*, 2015; Jakku *et al.*, 2019; van der Burg *et al.*, 2019; Wolfert *et al.*, 2017) and in some cases animal welfare issues related to SFT (Eastwood *et al.*, 2017a) all drive this farmer uncertainty. Supporting this, Wiseman *et al.* (2019) determine that the farmer's trust in SFT is linked to their willingness to share data, with farmers lacking trust in how their data is being managed by vendors. Thus, examining the farmer's perceptions of the competency, benevolence and integrity of the SFT vendor is critical.

2.8.5.4 Gender

The technology adoption decision, its influences and the continued use of technology differ according to gender (Graham, 2011; Skare and Blažević Burić, 2021; Venkatesh and Morris, 2000). Gender in this instance is defined as an individual's biological sex as opposed to gender as a social construct. Aguirre-Urreta and Marakas (2010) explain that differences in how and when genders adopt technology is due to personality, social and cultural factors. For example, Costa *et al.* (2001) determine that with regard to personality traits, women report themselves as having higher qualities of neuroticism, agreeableness, and openness to feelings, while men self-report higher qualities of assertiveness and openness to ideas. Women also exhibit higher levels of computer anxiety and lower levels of self-efficacy (ibid). In the development of UTAUT, Venkatesh *et al.*, (2003) determine that gender was a moderating influence on the relationship between performance expectancy and behavioural intention. Likewise, in their study of multimedia technology adoption, Skare and Blažević Burić (2021) find that gender plays a moderating role on the relationship between PU and the intention to adopt. The relationship is significantly higher for men than women.

Women have a lower and slower adoption rate of agricultural technologies than men (Ragasa, 2012; Ragasa *et al.*, 2014; Worku, 2016). Although male and female farmers are equally efficient and proficient when working as farm managers, female farmers tend to own smaller farms than men and also have less access to labour, land and resources which influences their technology adoption decisions (Morris and Doss, 1999; Quisumbing, 1995). Sociocultural norms also contribute to this unequal adoption rate of technologies within agriculture (Rola-Rubzen *et al.*, 2020), with men more likely to be the beneficiary of land transfer practices (Hall *et al.*, 2017). It should be noted that much of this research is conducted in developing nations with considerably less studies available in Europe. Of the studies available in Europe, Pfeiffer *et al.* (2020) evaluated public attitudes towards digital farming technologies in Germany and find that men have slightly higher positive attitudes towards the benefits of such technology than women. Conversely, Elena-Bucea *et al.* (2020) assessed the role of gender in European's adoption of digital technologies within the wider society and find that gender has no impact.

With regard to SFT adoption, Paustian and Theuvsen (2016) highlight that because farming is dominated by men, gender as a factor has largely been unexamined. This is supported by Budge and Shortall (2022) who outline that generally research focuses on the male farmer. Chuang *et al.* (2020a) determine that young, male farmers in Taiwan have a higher intention to adopt IoT technology on-farm than young, female farmers. Male farmers in China also have a slightly higher willingness to adopt drone technology than females (Zheng *et al.,* 2018). Groher *et al.* (2020) find that female farmers in Switzerland are less likely to adopt digital technologies in livestock production than male, although they did highlight the small sample size. Das *et al.* (2019) similarly cite gender as an influencing factor on SFT adoption for Irish farmers. Equally, Michels *et al.* (2020b) suggest that male farmers are more likely to use or consider using a drone on-farm than females. Interestingly, a similar study from Michels *et al.* (2019) examining smartphone adoption and use in agriculture by German farmers finds no significant difference by gender. In the case of farmers' intentions to use autonomous field robots, Rübcke von Veltheim *et al.* (2021) determine that gender has no influence. Indeed, Zeweld *et al.* (2017) and Chuang *et al.* (2020b) call for more research to understand the effect that gender has on the adoption behaviour of farmers. Understanding the differences in SFT adoption by gender is furthermore a considerable area to examine, given the fact that women and younger people are showing less of an interest in farming as a career choice (Unay-Gailhard and Brennen, 2022). This, along with the discourse in the literature, justifies a more in-depth examination.

2.8.5.5 Age

Age has a variable effect on farmers' technology adoption decisions. In their study, Giua *et al.* (2022) outline that age was not a statistically significant influence on farmers' intentions to adopt SFT. In a similar vein, studies from Daberkow and McBride (2003) and Robertson *et al.* (2011) demonstrate that the age of the farmer has little or no significant effect on adoption. Similarly, Lima *et al.* (2018) found that age did not influence the adoption of electronic identification tools in agriculture. Barnes *et al.* (2019a) deduce that age impacts adoption, but only for particular PAT such as those requiring machine guidance. However, Isgin *et al.* (2008) conclude that age influences PAT adoption, with younger farmers more likely to consider adoption. This is consistent with Cavallo *et al.* (2015) who found that younger farmers are more likely to be interested in the technology, where older farmers are considered more likely to adapt to technology. Aubert *et al.* (2012) and Groher *et al.* (2020) determine that age and the adoption of digital farming technologies are negatively correlated, with older farmers less likely to adopt the technology. Higgins and Bryant (2020) concur that age and technology adoption are related, with older farmers often lacking the interest to learn more about technology. Supporting this viewpoint, Tey and Brindal (2012) infer that older farmers are less likely to adopt SFT due to the long learning curve associated with its use, and the shorter time period available to them to take advantage of the rewards. Furthermore, Drewry *et al.* (2019) outline how age is a barrier to continued technology adoption. Morris *et al.* (2005) demonstrate that both age and gender moderate the relationship between the usefulness of the technology and the attitude towards using it. They call for more research in other organisational settings to examine the influence of gender and age. The literature therefore suggests that examining the influence of age is important, but that it may be moderating factor rather than a primary determinant of intention.

2.8.5.6 Education

Education level impacts adoption as those with a lower level of education have a lower probability of adopting SFT, which is linked to not having adequate knowledge or confidence in the technology (Caffaro and Cavallo, 2019; Paxton *et al.*, 2011; Pierpaoli *et al.*, 2013; Pivoto *et al.*, 2019). According to Marescotti *et al.* (2021), farmers who have a lower level of education are more likely to be technophobes and thus their attitude towards technology is lower than farmers with a higher level of education. Certainly, Jerhamre *et al.* (2022) cite a lack of education related to the technologies, but also to the data generated, as a considerable barrier to adoption. Fountas *et al.* (2005) also support this viewpoint by highlighting how a lack of technical knowledge is a significant barrier to adoption. When the technology in question is relatively new, Huffman (2001) suggests that education is an important determinant of adoption. However, if the farmer has previous experience with SFT, they will move to adopting an additional technology with greater ease (Michels *et al.*, 2020b). Thus, providing the farmer with the necessary skills to consider experimenting with SFT is key (Aubert *et al.*, 2012).

An additional challenge for the farmer is using the data generated by SFT to create meaningful information that can create a competitive advantage (Saiz-Rubio and Rovira-Más, 2020). Consequently, Cisternas *et al.* (2020) determine that the low adoption rate of PAT is due to the long-term investment required for implementation, but also farmers lacking the skills needed to operate such technologies. These skills are both managerial and technical, requiring specific education and training (Pathak *et al.*, 2019). As such, determining the education level of the farmer is important in understanding if there is any impact on the intention to adopt SFT.

2.8.6 Application of TAM in agriculture

Recent studies using TAM in an agricultural technology context include the adoption of green agricultural production technologies (Dai and Cheng, 2022), the acceptance of artificial intelligence in agriculture (Mohr and Kühl, 2021), the intention to adopt an online nutrient management plan (McCormack *et al.*, 2021), IoT intention adoption by young farmers (Chuang *et al.*, 2020a), the adoption of unmanned aerial vehicles for pesticide application (Zheng *et al.*, 2018), the adoption of sustainable organic dairy production (Naspetti *et al.*, 2017), the intention to use grassland management practices on dairy farms (Kelly *et al.*, 2015), precision agriculture adoption (Aubert *et al.*, 2012), agricultural specialists' intention to adopt precision agriculture (Rezaei-Moghaddam and Salehi, 2010) and dairy farming technologies (Flett *et al.*, 2004). Consequently, Venkatesh *et al.* (2007) conclude that TAM still compares favourably compared to other models of technology adoption, due to the widespread attention in the literature.

Table 2.4 outlines findings from agricultural studies that used TAM for a better understanding of technology adoption. For example, Flett *et al.* (2004) measured PU in terms of economic profit and time savings, while PEOU was measured in terms of understanding and learning. Attitude was not however included in their model. They find support for both constructs impacting BI and actual usage. However, limitations of the study are acknowledged, particularly the reliance on self-reporting. Naspetti *et al.* (2017) tested the relationships between PU, PEOU, Attitude, BI and also includes Subjective Norm as an additional construct. They demonstrate that 'relevant others' such as peer farmers and advisors influence the PU of the technology, which subsequently impacts BI. They conclude that PU does not need to be mediated by attitude in order for it to affect BI. Zheng *et al.* (2018) used the TAM to investigate the factors which influence farmers' intentions to adopt unmanned aerial vehicles for pesticide application. Chuang *et al.* (2020a) assess young farmers' intentions to adopt IoT technologies using the TAM constructs. They find that the intention to adopt the technology is influenced by PEOU and PU.

Table 2.4 Studies using TAM in agriculture

Authors & year	Context	Methodology	Findings	Further Research
Dai and Cheng (2022)	Farmers' intentions to use agricultural green production technology.	Online survey to farmers with 738 completed responses.	• PU and PEOU influences adoption behaviour • Social networks influence PU but not PEOU	Examine farmers' risk perception of agricultural green production technologies.
Castiblanco Jimenez *et al.* (2021)	Farmers' acceptance of an e-learning platform.	Online survey to farmers with 42 completed responses.	• PU has a strong influence on attitude. • PEOU influences PU. • PEOU has no effect on attitude. • PU influences BI • Attitude has a significant effect on BI.	Replicate the research with a larger sample size.
McCormack *et al.* (2021)	Farmer adoption of a nutrient management online plan.	Online survey to farmers with 358 responses.	• PU and PEOU are significant influencers of a farmer's intention to use a NMP. • The effect of PU on intention is stronger.	n/a

Authors & year	Context	Methodology	Findings	Further Research
Mohr and Kühl (2021)	Artificial Intelligence.	84 farmers surveyed with letter or online questionnaire.	• PEOU influences acceptance. • PEOU influences PU. • PU has no significant influence on acceptance. • Social norm has no significant influence on acceptance. • Attitude has no significant influence on acceptance.	Identify additional drivers and barriers to AI acceptance.
Negi and Nasreen (2021)	Adoption of an electronic trading portal.	Online survey to farmers with 370 responses.	• Attitude influences BI. • PU influences BI. • PU influences attitude. • PEOU influences attitude. • PEOU influences BI. • PEOU influences PU.	Extend the research to new locations, add in new constructs such as perceived economic wellbeing.
Rezaei *et al.* (2020)	Adoption of Integrated Pest Management (ecological conservation technology)	Online survey to 327 tomato growers.	• Attitude influences BI. • PU and PEOU influences ATT. • PEOU influences PU.	Further research to explain how demographic variables may affect farmers' ecological behaviour.
Chuang *et al.* (2020a)	IoT use among young farmers involved in field crop production.	Online survey to farmers with 241 responses.	• PEOU has an influence on the intention to adopt. • PU has an influence on the intention to adopt. • Sense of trust has an influence on the intention to adopt.	Extend to other agriculture contexts.
Caffaro *et al.* (2020)	SFT adoption (recording and mapping technologies and autonomously operated machines and connect tools).	Physical questionnaire to 314 male farmers.	• PU influences BI. • PEOU does not influence BI. • Attitude was not measured. • Also examined the influence of sources of information on PU & PEOU.	Longitudinal design with a consistent recording of the types of SFT information consulted. Use age and education as

Authors & year	Context	Methodology	Findings	Further Research
				control variables. Measure actual usage instead of BI.
Zheng *et al.* (2018)	Adoption of unmanned aerial vehicles (UAV) .	Online survey to farmers with 897 responses.	• PEOU impacts the decision to adopt. • PU impacts the decision to adopt.	Research on the cost effectiveness of using UAVs for agricultural Application.
Naspetti *et al.* (2017)	Sustainable Production Strategies among Dairy Farmers.	Online survey to farmers with 190 responses.	• PU was seen to be a driver of adoption. • PEOU influences adoption. • SN influences PU • Attitude towards dropped in the final model. • Influence of Subjective Norm on intention was not significant.	Further research is needed to validate the findings in other contexts.
Kelly *et al.* (2015)	Dairy Farmers' grassland management practices.	Online survey to dairy farmers with 389 responses.	• Farmer perceptions based on TAM (i.e., PU and PEOU) more accurately predict a positive intention.	Further research is necessary to understand the existing perceptions towards the use of grassland management practices.
Aubert *et al.* (2012)	Adoption of Precision Agriculture technologies.	Online survey to farmers with 483 responses.	• PEOU impacts the decision to adopt. • PU impacts the decision to adopt. • PEOU had no significant influence on PU.	Further exploration of the relationship between PEOU and PU.
Rezaei-Moghaddam and Salehi (2010)	Adoption of Precision Agriculture technologies by ag specialists.	Online survey to agriculture specialists with 705 responses received.	• PEOU has a positive impact on attitude. • PEOU has positive impact on PU. • PEOU has no direct effect on intention to adoption. • PEOU indirectly affects intention to	n/a

Authors & year	Context	Methodology	Findings	Further Research
			adopt through attitude. • PU has a positive direct effect on attitude to use. • PU has no direct effect on intention to adopt. • Attitude positively influences Intention.	
Adrian *et al.* (2005)	Adoption of Precision Agriculture technologies.	Online survey to agriculture producers with 85 responses.	• PEOU has no influence on PU. • PU did not directly affect the intention to adopt. • PEOU did not influence intention to adopt.	Further research on the newly introduced construct "perceived net benefit”.
Flett *et al.* (2004)	Adoption of Dairy Farming Technologies.	Online survey to dairy farmers with 985 responses.	• PEOU impacts the decision to adopt. • PU impacts the decision to adopt. • PEOU influences PU.	Longitudinal study recommended.

In summary, Table 2.4 and Section 2.8 has provided support for using TAM as a guiding lens for this study. Although each of the original constructs outlined such as PEOU, PU, Attitude and Behavioural Intention have considerable empirical support, the literature concludes that additional constructs such as personal innovativeness, trust and social influence are important to integrate with TAM to improve its explanatory power. Figure 2.2. therefore, summarises and represents the critical elements of this research.

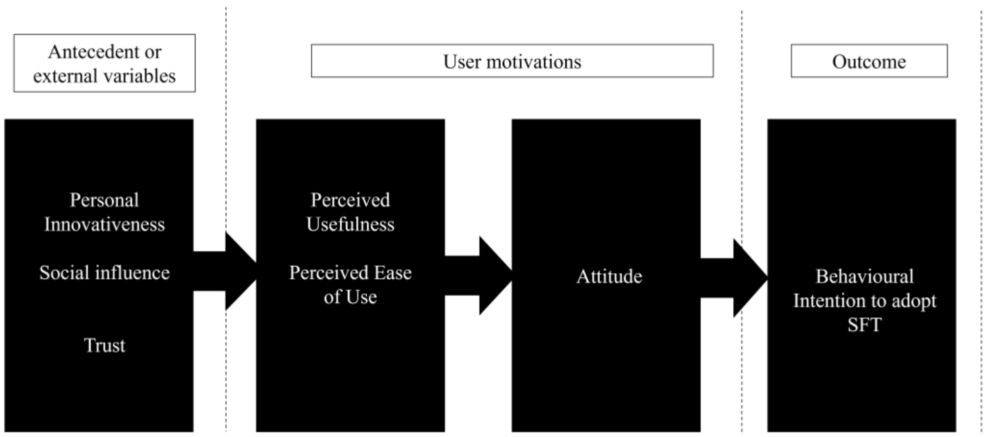

Figure 2.2 Critical elements of the research

2.9 Alternative Frameworks

Understanding intention and actual behaviour can be examined from both a cognitive and behavioural learning model approach. Behavioural learning models such as instrumental conditioning theory (Skinner, 1953) or classical conditioning theory (Pavlou, 1927) stipulate that behaviour occurs as a response to external stimuli which then promotes that learning has taken place (Schiffman and Kanuk, 2000). Cognitive learning models on the other hand explain how individuals are influenced and respond to stimuli and factors in the environment (Ratten, 2008). As this research is centred around understanding the influence of several internal and external factors on the farmer's intention to adopt SFT, it is argued that a cognitive learning model approach is more appropriate. The intention to adopt SFT is influenced by complex cognitive processes particularly related to the usefulness and ease of use of the technology. These perceptions are not well addressed by behavioural learning models which focus more on observable behaviours.

TRA, TPB, TAM, UTAUT and Social Cognitive Theory (SCT) all are examples of cognitive learning models (Ratten and Ratten, 2007). As outlined in Table 2.1 and discussed throughout this chapter, each of these theories could have been used as a guiding framework for this research. The Theory of Reasoned Action (TRA) includes behavioural intention as a variable; however, it was deemed not appropriate for this study as it excludes behaviours that are said to require specific skills or opportunities such as money, time or cooperation with other people (Hale *et al.*, 2003). It is argued that the adoption of SFT requires both capital and a specific skillset to enable adoption. The TRA also assumes that the individual has volitional control over the behaviour in question (Sok *et al.*, 2020) and is deemed not falsifiable as a theory (Ogden, 2003). The Theory of Planned Behaviour (TPB) which developed from the TRA has also received criticisms in terms of being less predictive of behaviour (Sniehotta *et al.*, 2014) and lacking evidence to determine its usefulness as a theory (Hardeman *et al.*, 2002). Mathieson (1991) further criticises the theory for not explaining the attitude construct particularly well. As TAM deals with the adoption of technology, it was considered more suitable than the TPB, which is viewed as more general.

The Diffusion of Innovation (DoI) theory was ruled out as a theoretical framework as, although it was developed with agriculture in mind, it is seen as not being sufficiently relevant for technological innovations (MacVaugh and Schiavone, 2010). In addition, Rogers (2003) himself explains that the theory is more relevant for studying implementation rather than adoption. Kuehne *et al*., (2017) deduce that the theory is better at conceptualising adoption, rather than predicting adoption. The Unified Theory of Acceptance and Use of Technology (UTAUT) is particularly relevant to understand and explain adoption of IT systems (Venkatesh *et al.*, 2003). The model contains four core constructs, four moderating variables, as well as the BI and use behaviour variables. Conversely, the complete theory is often overlooked in TA studies and subsets are used instead (Williams *et al.*, 2011). Bagozzi (2007a) criticises it for being overly complex, while Dwivedi *et al.* (2017) disapproves of the absence of the attitude construct. Moreover, van Raaij and Schepers (2008) outline that there are issues with how items and constructs are grouped and labelled. Finally, TAM has seen several amendments such as the extended TAM-TAM2 from Venkatesh and Davis (2000) which includes additional variables from social influence processes and cognitive instrumental processes. These include subjective norm, voluntariness, image, result demonstrability, job relevance, output quality and experience. However, TAM2 focuses mainly on the drivers of PU (Boughzala, 2014) and as such could be determined as a non-complete model (Zaineldeen *et al.*, 2020). It also drops the attitude construct which is important in understanding users' perceptions of technology (Holden and Karsh, 2010). TAM3 addressed the shortcomings of TAM2 and introduced a model which included the determinants of both the PU and PEOU construct. However, these expansions to the original TAM are criticised for being overly complex, less parsimonious and causing theoretical chaos (Benbasat and Barki, 2007).

A social cognitive theory (SCT) approach from Bandura (1986) could also have been adopted for this study. SCT stipulates that behavioural change happens when an individual feels that they have a sense of control, where both motivation and action are influenced by forethought (Luszczynska and Schwarzer, 2005). As such, behaviour is controlled by the individual's thought processes alongside factors in the external environment (Cooper and Lu, 2016). Marketing was one of the first disciplines to apply SCT to better understand consumer behaviour (Carillo, 2010). The self-efficacy concept from Bandura (1978) is central to the theory, implying that the individual's abilities and competencies predict behaviour (Prussia and Kinicki, 1996). The concept of outcome expectancies is also an important construct in SCT, relating to the individual's expectations regarding the consequences of their actions (Bandura, 1986). Intrinsically, expectations of a positive outcome are pointless if an individual doubts their ability to conduct the behaviour (Schunk and DiBenedetto, 2020). Socio-structural factors, such as social norms, physical environment and culture, are influenced by self-efficacy and in turn influence the individual's goals (Bandura, 1991). Consequently, SCT is based on the idea of triadic reciprocal determinism where personal factors, environmental factors and behavioural factors are consistently interacting and influencing behaviour (Woodcock and Tournaki, 2022). This is one of the key differences between SCT and TAM/TPB, with SCT focusing on a bidirectional perspective while TAM/TPB are determined by a unidirectional perspective towards causal relationships (Carillo, 2010).

The theory was originally focused on physical and emotional well-being (Bandura, 1998) but has been cited as useful in the context of technology adoption (Ratten and Ratten, 2007). For example, Compeau and Higgins (1995) used SCT as the foundation for their theory related to the adoption of computer technology, Ratten and Ratten (2007) used it to determine attitudes towards cloud computing, Agarwal *et al.* (2013) adopted SCT for their study of personal health records, while Boateng *et al.* (2016) used it to assess the determinants of internet banking intentions. While the SCT is a useful theory, it is more focused on the processes of learning (Jenkins, 2018) and is often criticised for being too broad and not being a unified theory (Beauchamp *et al.*, 2019). Thus, although SCT is a broad and comprehensive theory encompassing several social and cognitive processes which influence behaviour, it is argued that it does not provide the level of specificity needed to address the factors, such as PU and PEOU of SFT, which influence the farmer's intention to adopt such technology.

2.10 Conclusion

The chapter presents the foundational, theoretical framework guiding this research. In particular, the literature related to Organisational Buying Behaviour and Technology Adoption were reviewed both in a wider context and in relation to the farmer's behaviour. The importance in understanding the buying situation or experience level (i.e., non-adopters vs existing adopters), the buying centre (i.e., conceptualised as social influence in this study) and its influence on the intention to adopt SFT, and the key factors influencing behavioural intention was determined. The literature also highlighted the importance of trust within an OBB context.

Technology adoption studies suggest that the Perceived Usefulness and Perceived Ease of Use of the technology are considerable influences on the attitude towards using the technology and the intention to adopt. In addition, PU directly influences the BI to adopt the technology. However, the literature shows that personality traits, trust in the vendor and social influence are critical elements which are largely unexamined in the context of SFT. Further research is necessary to empirically test how these factors influence the farmer's BI to adopt SFT. To address these identified research gaps, a conceptual model is needed to study the key factors influencing the behavioural intention to adopt SFT. The subsequent chapter focuses on these factors in detail with a view to identifying potential relationships between them and to develop a set of hypotheses and associated conceptual model.

Chapter 3: Conceptual Model Development and Proposed Hypotheses

3.1 Introduction

In Chapter 2, multiple literatures and theoretical elements were reviewed. Importantly, the literature review outlined the need for more empirical studies on the factors influencing farmers' behavioural intention (BI) to adopt SFT, due to the limited or slower than expected adoption of such technologies (de Oca Munguia and Llewellyn, 2020; Eastwood and Renwick, 2020; Pathak *et al.*, 2019; Pivoto *et al.*, 2019; Shang *et al.*, 2021). The Technology Acceptance Model (TAM) was selected as an appropriate framework for this study, while elements of Organisational Buying Behaviour (OBB) were also used as a guiding lens for the research. However, it was observed that TAM fails to account for important variables such as social influence, trust and personality (Chen *et al.*, 2002; Yousafzai *et al.*, 2007b). Thus, examining TAM, the Theory of Reasoned Action (TRA), the Theory of Planned Behaviour (TPB) and their deficiencies, highlighted the need for an integrated model to determine the influence of key factors on farmers' behavioural intention to adopt SFT.

Rose *et al.* (2018c), Bukchin and Kerret (2018) and Ali *et al.* (2017) note a paucity in the literature related to how farmer personality traits impact behaviour. Thus, personal innovativeness in the IT domain was selected as a suitable personality trait to examine. This was based on its relevance to new technologies, as outlined by Agarwal and Prasad (1998) and due to it being a stable personality trait (Ali *et al.*, 2017; Rosen, 2004). Furthermore, Jayashankar *et al.* (2018) deduce that the role of the farmer's network in facilitating technology adoption requires further examination, resulting in social influence being investigated further. In addition, trust has not been assessed as an underlying structure to explain TAM (Bagozzi, 2007a). Consequently, the literature review highlighted that trust in the SFT vendor was a critical factor hampering its adoption, due to issues with vendor promises and reliability (Khanna *et al.*, 2021). These additional variables are incorporated into TAM to create an integrated, conceptual model of the key factors influencing the farmer's behavioural intention to adopt SFT, as presented in Figure 3.1. Section 3.2 briefly reintroduces the constructs discussed in Chapter 2. Section 3.3 discusses the hypothesised relationships between these variables and presents the overall conceptual model. Section 3.4 presents the control variable used in the study and outlines its proposed influence on the hypothesised relationships. Section 3.5 concludes the chapter.

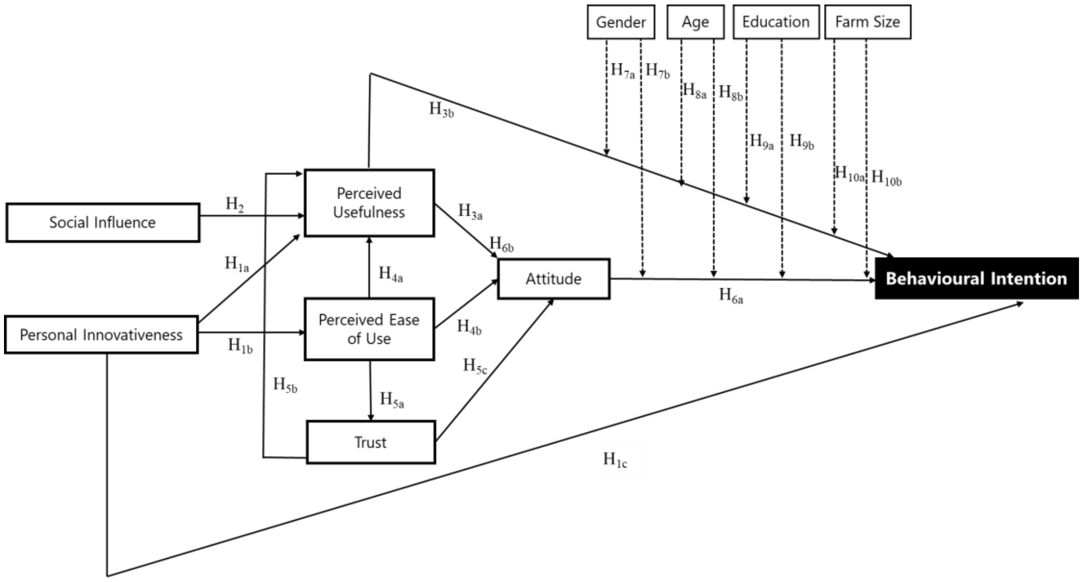

Figure 3.1 Integrated Conceptual Model

3.2 Antecedents to the behavioural intention to adopt SFT

A summary of the constructs, their acronyms, a corresponding definition and the theory associated with the construct are provided in Table 3.1 below. As outlined, the basis of the conceptual model in this research is taken from TAM, which was developed to understand and predict how users adopt and accept new technologies or systems (Davis, 1986). Potential weaknesses in the established models discussed in Section 2.7.1 led to the development of a novel, integrated model that incorporates factors such as social influence, personal innovativeness, and trust. The emerging conceptual model recognises that the adoption of technology is multifaceted, involving attitudes and perceptions but also social influence, individual personality traits, and trust. By integrating these constructs, the conceptual model offers a more comprehensive perspective of the factors influencing farmers' behavioural intention to adopt SFT and the relationships between these factors.

Table 3.1 Definition of Principal Research Constructs

Construct	Definition	Theory/ Model	Source
Behavioural Intention (BI)	An individual's subjective probability that he or she will perform a specified behaviour.	TAM/ TRA/ TPB	Fishbein and Ajzen (1975, p. 288).

Construct	Definition	Theory/ Model	Source
Attitude (ATT)	An individual's degree of evaluative affect toward the target behaviour.	TAM/ TRA/ TPB	Fishbein and Ajzen (1975, p. 216).
Perceived Ease of Use (PEOU)	The degree to which an individual believes that using a particular system would be free of physical and mental effort.	TAM	Davis (1986, p. 26).
Perceived Usefulness (PU)	The degree to which an individual believes that using a particular system would enhance his or her job performance.	TAM	Davis (1986, p. 26).
Social Influence (SI)	The degree to which an individual perceives that important others believe he or she should use the new system.	TAM2/TPB/ TRA/ UTAUT	Venkatesh *et al.* (2003, p. 451).
Trust	The willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other part.	Integrative Model of Organizational Trust	Mayer *et al.* (1995, p. 714).
Personal Innovativeness in the domain of Information Technology (PIIT)	The willingness of an individual to try out any new information technology.	PIIT	Agarwal and Prasad (1998, p. 206).

The literature review also suggested that age, education, gender and farm size constitute potential moderating variables which warrant inclusion in the conceptual model.

3.3 Research Hypotheses

In the following sections, the antecedents to the BI to adopt SFT are outlined, and the associated hypotheses are discussed. This is based on the literature review presented in Chapter 2 and the critical elements of the research, as illustrated in Figure 2.2.

3.3.1 The influence of Personal Innovativeness in the domain of Information Technology (PIIT) on Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) and Behavioural Intention (BI)

The innovativeness of business-leaders has a considerable influence on the adoption of technologies within organisations (Thong, 1999). As with other occupations, farmers differ regarding when, or if, they adopt an innovation based on their level of innovativeness and entrepreneurship (Diederen *et al.*, 2003). As outlined in Section 2.8.5.2, Personal Innovativeness in the domain of IT (PIIT) can influence adoption of new technologies. Agarwal and Prasad (1998) deduce that there is a significant relationship between PIIT and PU, and PIIT and PEOU. Similarly, Lu *et al.* (2005) deduce that individuals showing higher levels of PIIT have more positive beliefs about Wireless Internet services via mobile technology (WIMT), influencing both PEOU and PU. However, they deduce that PIIT has no impact on the intention to adopt WIMT. Lewis *et al.* (2003) find that PIIT significantly influences the PEOU and PU of IT systems among public university faculty. In the context of nursing, Fagan *et al.* (2012) explain that PIIT had a significant influence on both the PU and PEOU of virtual reality simulation technology, alongside the intention to adopt. Hwang (2014) examined the role of PIIT on employees' adoption of Enterprise Resource Planning Systems and found that PIIT influences both the PEOU and PU of the technology.

Other studies either contradict these previous studies discussed or fail to examine the influence of PIIT on both the PU and PEOU constructs. For example, according to Lu (2014), PIIT has a direct effect on the PEOU of mobile commerce among undergraduates and graduates in the USA, but no effect on PU. Similarly, Robinson *et al.* (2005) determine that PIIT impacts the PEOU of technologies such as voicemail, customer contact software, cell phone etc among salespeople, but has no influence on PU. It is argued, however, that these technologies may not significantly enhance an individual's job performance or efficiency. In the context of personal digital assistant (PDA) acceptance by healthcare professionals in the US, Yi *et al.* (2006b) reason that PIIT has a significant effect on PEOU; but the relationship between PIIT and PU was not tested. Sagnier *et al.* (2021) find the relationship between PIIT and PU to be significant in the context of virtual reality adoption in an aeronautical setting, but there was no significant relationship between PIIT and PEOU.

Jackson *et al.* (2013) examined the influence of PIIT on hospital administrators' intention to use an e-commerce purchasing system. They found that PIIT has a strong influence on intention but only through the mediating variables such as innovation characteristics, social influence, and personal control perception. The TAM constructs were not tested. Sagnier *et al.* (2021) determine that there is a significant relationship between PIIT and BI. Similarly, Patil *et al.* (2020) explain that PIIT impacts consumers' intention to adopt mobile payments in India.

In an agricultural context, Mohr and Kühl (2021) demonstrate that there is a significant, positive relationship between PIIT and PU as well as PIIT and PEOU in their study of artificial intelligence (AI) in German agriculture. Thus, it suggests that farmers who demonstrate a higher level of innovativeness are more likely to develop positive perceptions about SFT. The authors find no support for PIIT influencing the acceptance of AI, but did note that this may have been due to the relatively small size of the sample. Emmann *et al.* (2013) investigated the effect of personal innovativeness on farmers' acceptance of biogas innovation and found it to be significant. However, their operationalisation of personal innovativeness was different to the PIIT construct and they examined acceptance rather than adoption. Similarly, Aubert *et al.* (2012) determined that personal innovativeness impacts the adoption of PAT. Their operationalisation was taken from the Taylor and Todd (1995) self-efficacy measure which focuses on feeling comfortable using technology, the individual's ability to use the technology on their own, and the ability to use technology without help. This is somewhat similar to the PIIT construct, as discussed in Section 2.8.5.2, but PIIT is however more focused on experimenting with new technologies.

An alternative perspective is that PIIT can moderate the relationship between PU and behavioural intention. The relationship has been hypothesised by several authors (Agarwal and Prasad, 1998; Alkawsi *et al.*, 2021; Dabholkar and Bagozzi, 2002; Okumus *et al.*, 2018), however there is limited empirical support for this relationship. This alternative theory is tested in Chapter 5, Section 5.6.3. Therefore, based on these findings, the following hypotheses arise:

H_{1a}: Personal innovativeness has a positive effect on the Perceived Usefulness of Smart Farming Technology.

H_{1b}: Personal innovativeness has a positive influence on the Perceived Ease of Use of Smart Farming Technology.

H_{1c}: Personal innovativeness has a positive direct effect on the Behavioural Intention to adopt Smart Farming Technology.

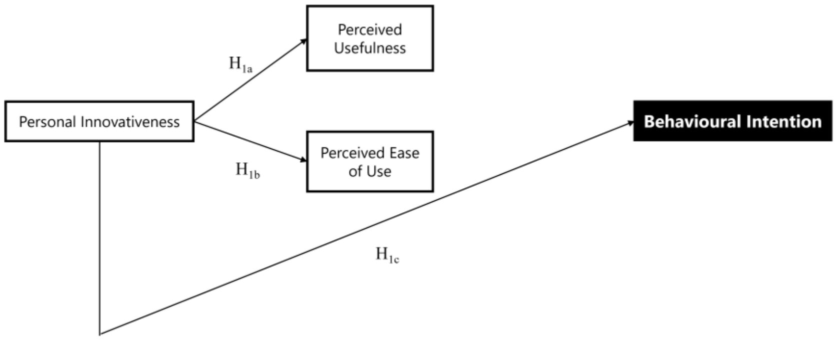

Figure 3.2 Hypothesis One

3.3.2 The effect of Social influence (SI) on Perceived Usefulness (PU)

Social influence relates to an individual's perceptions that significant others believe that they should carry out a particular act or behaviour (Ajzen and Fishbein, 1980). The construct is explained and discussed in Section 2.8.5.1. In the extant literature, SI is seen to significantly influence the PU of a technology (Dutot, 2015; Nabhani *et al.*, 2016; Terzis *et al.*, 2012; Vanduhe *et al.*, 2020; Wang and Chou, 2014; Weng *et al.*, 2018; Wu and Chen, 2017; Zhang *et al.*, 2020). While the original TAM did not include SI, TAM2 from Venkatesh and Davis (2000) recognises the importance of including the construct. They found that SI has a direct influence on the PU of the technology, arguing that an individual's perception of the usefulness of technology will increase based on information from their social groups. In support of this, Naspetti *et al.* (2017) find that the subjective norm (SN), which is similar to SI, has a direct influence on PU in their study of dairy farmers' adoption of sustainable production strategies. Iskandar and Yusep Rosmansyah (2018) find that the SN influences the PU of a mobile learning system for farmers. Castiblanco Jimenez *et al.* (2020) determine in their literature review of TAM that social influence has a more significant influence on PU than PEOU, in the case of farmers' acceptance of an e-learning platform.

In other contexts, Yi *et al.* (2006b) deduce that SI has a positive influence on a professional's PU of a personal digital assistant. In relation to an individual's adoption of e-government services, Horst *et al.* (2007) find empirical support for SN influencing PU. In addition, Lin *et al.* (2003) determine that SN has a significant influence on law enforcement officers' PU of an online system. Lu *et al.* (2005) find that SI influences the PU of wireless Internet services via mobile technology but has no influence on intention to adopt. Jackson *et al* (2013) outline how SI influences the PU of an e-commerce purchasing system but not the PEOU. Furthermore, Schepers and Wetzels (2007) deduce in their meta-analysis of TAM that SN has a direct positive effect on PU and BI. They also demonstrated a positive relationship between SN and attitude; however, it did not pass the fail-safe N test, which represents the number of studies required to challenge the statistical significance of averages with a meta-analysis.

Venkatesh and Davis (2000) conclude that SN does not have an influence on the behavioural intention to adopt when the technology in question is adopted voluntarily. However, the relationship is significant when adoption of the technology is mandated. It is argued that it is unlikely that the use of SFT would be mandated to farmers; its use is more likely to be encouraged or incentivised by policymakers. Conversely, in their study of the adoption of PAT in China, Li *et al.* (2020b) determine that SI has no significant impact on the intention to adopt. Similarly, Fox *et al.* (2021) find no support for SI influencing the BI to adopt a mobile digital platform by family-operated farm enterprises.

Based on these empirical studies, the following hypothesis emerges, as illustrated in Figure 3.3:

H_2: Social influence has a direct influence on the Perceived Usefulness of Smart Farming Technology.

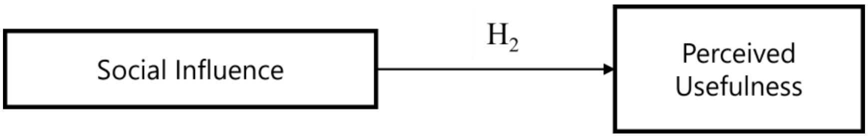

Figure 3.3 Hypothesis Two

3.3.3 The impact of Perceived Usefulness (PU) on Attitude and Behavioural Intention

Perceived Usefulness, as outlined in Section 2.8.2, is described as the "*degree to which a person believes that using a particular system would enhance his or her job performance*" (Davis, 1989, p. 320). This construct is seen as being the most influential belief on technology adoption and acceptance (Sun and Zhang, 2006; Taylor and Todd, 1995; Yousafzai *et al.*, 2007a). PU firstly has a causal effect on the attitude towards using the technology (Davis, 1989). Although, attitude was dropped from the final TAM model, in a later study on managerial employees' intention to adopt an e-mail system and text editor, Davis (1993) found that PU had a significant effect on attitude. In their meta-analysis of TAM, Yousafzai *et al.* (2007b) conclude that PU influences the attitude and intention towards adoption. The relationship is also supported in several consumer and organisational studies (Karahanna *et al.*, 1999; Lin and Lu, 2000; Lymperopoulos and Chaniotakis, 2005; Malhotra and Galleta, 1999; Phillips *et al.*, 1994; Pijpers *et al.*, 2001). Detailing additional studies, the PU of online food purchasing channels influences consumers' attitudes towards adoption (Nguyen *et al.*, 2019). The PU of mobile application, Uber, influences consumers' attitudes towards adopting it (Min *et al.*, 2018). Kim and Woo (2016) determines that the PU of quick response codes for food traceability systems impacts attitude towards adoption. Yang (2005) outlines how the PU of mobile commerce has a positive effect on consumers' attitudes towards adoption. Renny *et al.* (2013) conclude that PU influences consumers' attitudes towards online airlines ticket purchase. Furthermore, in a B2B setting, Obal (2013) concludes that PU influences the intention to adopt disruptive technology. The relationship is also supported by Kanchanatanee *et al.* (2014) in their examination of businesses' intention to use e-marketing services, while Weng *et al.* (2018) concludes that PU influences teachers' attitudes towards using multimedia technologies.

In an agricultural context, Rezaei *et al.* (2020) examined farmers' intentions to adopt an Integrated Pest Management system (ecological conservation technology) and found that PU influences attitude. Negi and Nasreen (2021) reason that there is a positive relationship between PU and attitude, with regard to farmers adopting an electronic trading portal. Castiblanco Jimenez *et al.* (2021) find that PU influences farmers' attitude towards using an e-learning platform. Iskandar and Yusep Rosmansyah (2018) outline that there is a significant relationship between PU and attitude when examining farmers' intentions to use a mobile learning system. Similarly, Sayruamyat and Nadee (2020) deduce that PU impacts the attitude towards using an AgriMap mobile application. Folorunso and Ogunseye (2008) find that both PU and PEOU affect agriculturists' attitude towards the use of a knowledge management system. In addition, Tohidyan Far and Rezaei-Moghaddam (2017) deduce that PU influences attitude in their study of Iranian agricultural consultants' intentions towards using precision agriculture. Finally, Rezaei-Moghaddam and Salehi (2010) find that the PU of precision agriculture affects agricultural specialists' intention to use the technology.

Furthermore, Davis *et al.* (1989) postulate that PU has a direct effect on behavioural intention. Consequently, in their meta-analyses of TAM, King and He (2006) and Yousafzai *et al.* (2007b) determine that the relationship between PU and BI is particularly strong. Consistent with TAM, Flett *et al.* (2004) find that the PU of the technology influences the farmer's intention to adopt dairy farming technology. They find that PU is more important to farmers than PEOU. Similarly in a SFT context, Caffaro *et al.* (2020) suggest that PU influences BI, but there is no relationship between PEOU and BI. Modh Suki and Modh Suki (2011) conclude that PU is a major determinant of BI with direct effect. However, Adrian *et al.* (2005) find that PU has an indirect influence on the BI to adopt precision technologies. Their study includes a 'Perceived Net Benefit' (PNB) construct which they described as the belief that the technology will provide a greater value than it costs. Nonetheless, they find support for PU having an indirect effect on BI, mediated by PNB. Thus, the following hypotheses, as shown in Figure 3.4 are proposed:

H_{3a}: The Perceived Usefulness of SFT has a positive influence on the Attitude towards using Smart Farming Technology.

H_{3b}: The Perceived Usefulness of SFT has a positive direct effect on the Behavioural Intention to adopt Smart Farming Technology.

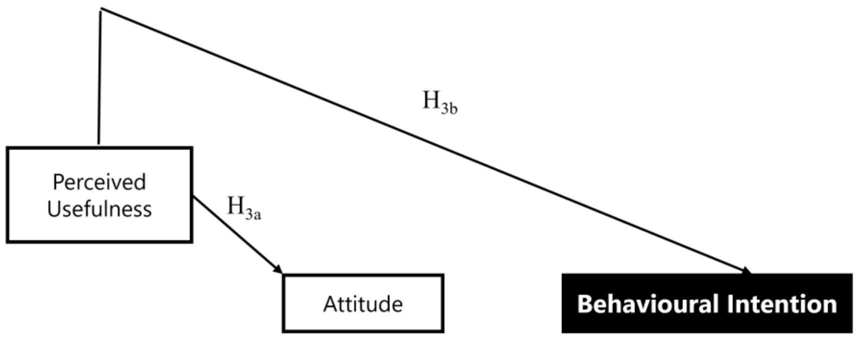

Figure 3.4 Hypothesis Three

3.3.4 The influence of Perceived Ease of Use (PEOU) on PU and Attitude

As detailed in Section 2.8.3, Perceived Ease of Use (PEOU) refers to "*the degree to which a person believes that using a particular system would be free of effort*" (Davis, 1989, p. 320). Davis (1986) posits that PEOU has a significant direct effect on PU, by explaining that if a technology is easy to use, the user's job performance will thereby increase. This relationship has received considerable empirical support in the literature (Jones *et al.*, 2002; Mathieson, 1991; Saadé and Bahli, 2005; Taylor and Todd, 1995; Venkatesh and Davis, 2000). Equally in their meta-analyses of TAM, King and He (2006) and Yousafzai *et al.* (2007a) also discern considerable support for the relationship between PEOU and PU being positive. Schepers and Wetzels (2007) determine that PEOU is important for new and complex technologies, which is it argued represents SFT. In support, Aubert *et al.* (2012) conclude that the PEOU of precision agriculture technology is an important construct to examine. Castiblanco Jimenez *et al.* (2021) explain that the PEOU of an e-learning system influences farmers' perceptions of its usefulness. The perceived usefulness of AI in agriculture is influenced by the perceived ease of use of the system, according to Mohr and Kühl (2021). Similarly, Negi and Nasreen (2021) determine that farmers' PU of an e-trading platform is influenced by its PEOU. Rezaei-Moghaddam and

Salehi (2010) establish that there is a strong correlation between PEOU and PU. Finally, Flett *et al.* (2004) conclude that there is a statistically significant association between the PEOU of dairy farming technologies and the PU.

Furthermore, PEOU is a direct determinant of attitude, as outlined by the original TAM (Davis, 1986; Venkatesh, 2000). However, attitude was later dropped from the model but in a later study, Davis (1993) finds support for PEOU influencing attitude, although the relationship is not as significant as PU and attitude. Equally, Yousafzai *et al.* (2007b) determine that PEOU has a direct effect on attitude. In their meta-analysis, they find the relationship to be significant in 82 per cent of cases (36 studies). Rezaei *et al.* (2020) find that there is a direct relationship between PEOU and attitude towards adopting an ecological conversation technology. The relationship is also supported by Negi and Nasreen (2021) while Wu *et al.* (2011), Rezaei-Moghaddam and Salehi (2010) and Folorunso and Ogunseye (2008) conclude that there is a strong correlation between both PU and attitude and PEOU and attitude.

However, the relationship between PEOU and BI is insignificant (Adrian *et al.*, 2005; Davis, 1989). From their meta-analysis of TAM, King and He (2006) similarly conclude that the major effect of PEOU on BI is through PU, rather than a significant direct effect. This was supported by Obal (2013) in a B2B setting, while Sun and Zhang (2006) concur that PEOU is not stable in predicting BI.

Therefore, the following is posited:

> *H_{4a}: The Perceived Ease of Use of Smart Farming Technology has a positive effect on the Perceived Usefulness of Smart Farming Technology.*
>
> *H_{4b}: The Perceived Ease of Use of Smart Farming Technology has a positive effect on the Attitude towards using Smart Farming Technology.*

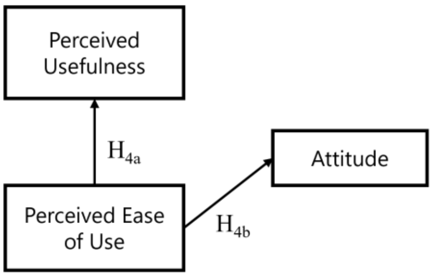

Figure 3.5 Hypothesis Four

3.3.5 The influence of Trust on Perceived Usefulness and Attitude and the influence of PEOU on Trust

Trust plays an important role in B2B settings by minimising risk and uncertainty (Doney and Cannon, 1997; Kemp *et al.*, 2018; Morgan and Hunt, 1994). Trust relates to the trustor's perceptions of the integrity, competency and benevolence of the trustee (Mayer *et al.*, 1995). In the context of SFT, trust in the vendor is a major concern for many farmers due to uncertainty regarding the value of implementation, alongside data ownership issues (Jakku *et al.*, 2019). This is supported by Fox *et al.* (2021) who determine that trust in the technology provider influences farmers' adoption and continued use of a digital platform. Trust has been successfully integrated with TAM in several studies, as outlined in Table 2.3 in Section 2.8.5.3. In the model of Trust and TAM from Gefen *et al.* (2003), trust is perceived as an antecedent of PU, while PEOU is an antecedent of trust. Several researchers have validated these relationships and suggest that PEOU has a positive influence on trust (Ainissyifa *et al.*, 2018; Belanche *et al.*, 2012; Herzallah and Mukhtar, 2016; Lee, 2009; Tung *et al.*, 2008) and trust influences PU (Belanche *et al.*, 2012; Dhagarra *et al.*, 2020; Lee, 2009; Pavlou, 2003; Tung *et al.*, 2008; Wu and Chen, 2005; Zhang *et al.*, 2021). Lin (2006) outlines how a user's perceptions of the ease of use influences their trusting beliefs. Furthermore, examining trust across several contexts such as the adoption of e-government services, e-commerce technology, autonomous vehicles and Internet banking also find supports for the relationships discussed (Belanche *et al.*, 2012; Hegner *et al.*, 2019; Pavlou, 2003; Suh and Han, 2002).

Alternatively, several researchers stipulate that PU affects Trust (Amin *et al.*, 2014; Benamati *et al.*, 2010; Li and Yeh, 2010; Roca *et al.*, 2009; Suh and Han, 2002). This alternative theory of PU influencing trust, rather than trust influencing PU is tested in Chapter 5, Section 5.6.3.

Furthermore, trust has a direct influence on attitude (Suh and Han, 2002; Wu *et al.*, 2011; Zhang *et al.*, 2021). In their meta-analysis of the impact of trust on TAM, Wu *et al.* (2011) determine that the relationship between trust and attitude is the least tested. They examined the relationships between all of the TAM constructs, including the influence of Trust on PU, PEOU, attitude and BI. They conclude that there is a relationship but the correlation between trust and attitude is the weakest, followed by trust and PEOU. Conversely, Pavlou (2003) posits that there is a general consensus in the literature that trust is related to positive attitudes.

Thus, the following is expected:

H_{5a}: The Perceived Ease of Use of Smart Farming Technology has a direct influence on Trust in the SFT vendor.

H_{5b}: Trust in the SFT vendor has a positive influence on the Perceived Usefulness of Smart Farming Technology.

H_{5c}: Trust in the SFT vendor has a direct influence on the Attitude towards using Smart Farming Technology.

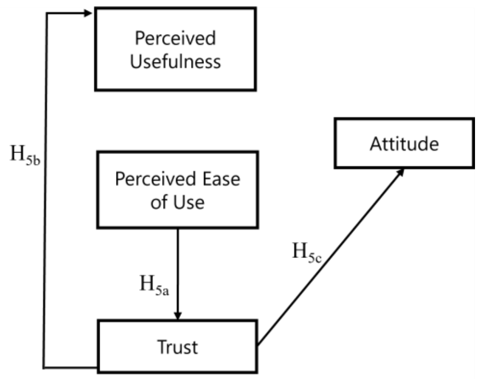

Figure 3.6 Hypothesis Five

3.3.6 The effect of Attitude (ATT) on Behavioural Intention

In the original TAM, the attitude towards using a technology partially mediates the effect of PU and PEOU on BI (Davis, 1986). However, ATT was dropped from the final TAM to deliver a more parsimonious model (ibid). López-Bonilla and López-Bonilla (2017) find support for including ATT in TAM studies, showing that its inclusion results in a better model. They further determine that ATT is a necessary variable to include when measuring BI. Moreover, Wu *et al.* (2011) outline that although it has become more commonplace to exclude ATT from TAM, it is still an important factor. Their meta-analysis of TAM determines that there is a strong correlation between ATT and BI. Ursavaş (2012) tested the role of ATT in students' computer usage by comparing two versions of their model: one with ATT and one without. The author determined that ATT towards use did not contribute to the variance in usage, but it does have a significant influence on BI, especially where the use of technology is voluntary. Lau and Woods (2008) also determine that ATT is an important construct in TAM.

The importance of including attitude with TAM is highlighted by Schepers and Wetzels (2007) who find that both PU and PEOU have a significant effect on ATT with the relationship between PU and ATT being stronger. Equally, Wu *et al.* (2011) conclude from their meta-analysis that ATT is an important construct in TAM and find support for there being a strong correlation between PU and ATT, PEOU and ATT, and ATT and behavioural intention. As previously outlined, Negi and Nasreen (2021) and Rezaei *et al.* (2020) find that PU and PEOU both influence ATT in an agricultural technology adoption context. Rezaei-Moghaddam and Salehi (2010) find that PU and PEOU have an indirect influence on BI, mediated through ATT. The alternative theory of removing ATT from the model is tested in Chapter 5, Section 5.6.3.

ATT has a direct effect on behavioural intention (Davis, 1986; Fishbein and Ajzen, 1975; Kim *et al.*, 2009). Certainly, several researchers have empirically tested and found support for the positive relationship between attitude and behavioural intention (Dwivedi *et al.*, 2017; Tama *et al.*, 2021; Taylor and Todd, 1995; Tohidyan Far and Rezaei-Moghaddam, 2017; Verma *et al.*, 2018). These studies use both TAM and TPB when assessing the relationship. Yousafzai *et al.* (2007b) conclude that the strongest correlations between attitude, PU, PEOU, and intention is between ATT-BI. In the context of agriculture, farmers' intentions to use Integrated Pest Management technologies is significantly influenced by their ATT towards such technologies (Rezaei *et al.*, 2020). Similarly, Castiblanco Jimenez *et al.* (2021) conclude that ATT is the strongest driver of a farmer's BI to use an e-learning platform. In other contexts, such as teachers' adoption of multimedia technologies, Weng *et al.* (2018) find that the relationship between ATT and BI is stronger than PU and BI. Modh Suki and Modh Suki (2011) determine that ATT has a significant positive relationship with consumers' BI to use 3G mobile services. In their study of small businesses' BI to use e-marketing, Kanchanatanee *et al.* (2014) found that attitude was a significant determinant of BI. Raza *et al.* (2017) also find support for ATT having a direct effect on BI for the use of mobile banking services. Zhao *et al.* (2018) also conclude that ATT has a significant effect on the BI to adopt personalised business modes, while ATT also has a partial mediating role between PU and BI.

Thus:

H_{6a}: Attitude towards using SFT has a direct influence on the Behavioural Intention to adopt Smart Farming Technology.

H_{6b}: Attitude towards using SFT mediates the relationship between PU and the Behavioural Intention to adopt Smart Farming Technology.

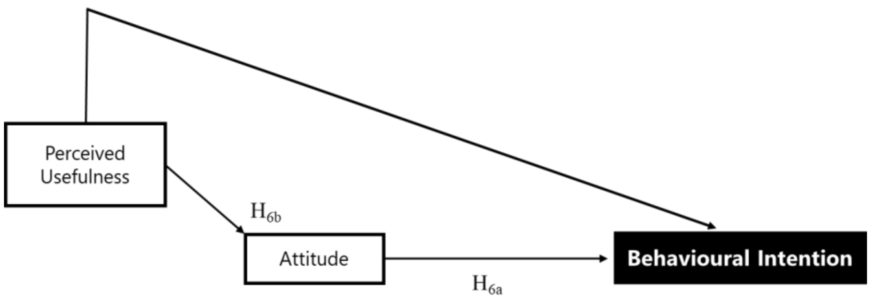

Figure 3.7 Hypothesis Six

3.3.7 The influence of Moderating Variables on the relationship between Perceived Usefulness and Behavioural Intention, and Attitude and Behavioural Intention

3.3.7.1 Gender

Section 2.8.5.4 details how gender influences technology adoption. In agriculture, women adopt technologies at a slower rate than men (Ragasa, 2012; Ragasa *et al.*, 2014; Worku, 2016). However, such technologies are recognised as a potential solution to narrowing the gender gap in agriculture (Huyer, 2017). In their meta-analysis on the influence of gender on attitudes towards technology use, Cai *et al.* (2017) explain that generally men have more favourable attitudes to technology than women. Furthermore, Venkatesh *et al.*, (2000) determine that men are more likely to be influenced by their attitude towards using the technology than women. Several researchers have supported the moderating influence that gender has on the relationship between PU and intention or performance expectancy and intention (Chang *et al.*, 2019; Gefen and Straub, 2000; Nahar, 2022; Terblanche and Kidd, 2022; Venkatesh *et al.*, 2000). Performance expectancy is a construct used in the UTAUT model and is similar to PU (Kelly *et al.*, 2023). Morris *et al.* (2005) find support for the hypothesis that gender moderates the relationship between attitude and intention and PU and intention. Their study focused on the Theory of Planned Behaviour, but they state that their findings are also applicable to studies using TAM. Similarly, Park *et al.* (2019) find that the influence of PU on intention to use is moderated by gender, with the relationship stronger for men.

However, the influence of gender has also been challenged. Kim (2016) outlines that many of the studies that show that gender has an impact an adoption were conducted prior to 2000. Wong *et al.* (2011) determine that gender has no significant influence on adoption of email services. Kim (2016) find that gender does not moderate the relationship between PU and BI of a hotel tablet application. Li *et al.* (2008) similarly deduce that gender has no influence on the adoption of m-commerce.

However, based on the key studies from Venkatesh and Davis (2000) and Gefen and Straub (2000) the following hypotheses are proposed:

H_{7a}: The relationship between Perceived Usefulness and the Behavioural Intention to adopt SFT is moderated by Gender.

H_{7b}: The relationship between Attitude and the Behavioural Intention to adopt SFT is moderated by Gender.

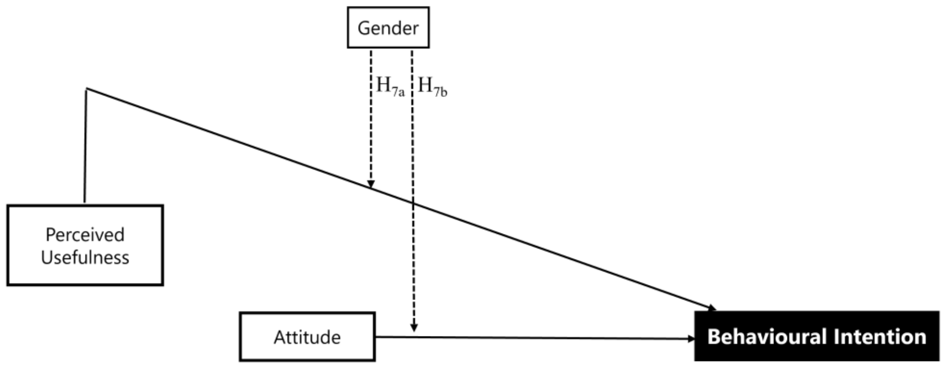

Figure 3.8 Hypothesis Seven

3.3.7.2 Age

Age is an important factor to examine, as farmers, in general, are an ageing population (Debonne *et al.*, 2022). The impact of age on the adoption of SFT has been previously discussed in Section 2.8.5.5. Overall, the extant literature reveals that the effect of age on SFT adoption is conflicted. Several studies determine that age has no impact on farmers' adoption of SFT or PAT (Daberkow and McBride, 2003; Giua *et al.*, 2022; Lima *et al.*, 2018; Robertson *et al.*, 2011). Other studies deduce that age impacts adoption, with younger farmers more likely to adopt new technologies than older farmers (Aubert *et al.*, 2012; Cavallo *et al.*, 2015; Groher *et al.*, 2020; Higgins and Bryant, 2020; Isgin *et al.*, 2008).

Castiblanco Jimenez *et al.* (2020) suggest that age and gender are the most common moderating factors to examine with TAM. As with gender, the relationship between PU and intention is moderated by age (Venkatesh and Davis, 2000; Venkatesh *et al.*, 2003). Ahmad *et al.* (2010) determine that age has a significant impact on the causal relationships within TAM in their study of acceptance of computer-based technologies by members of faculty. Morris *et al.* (2005) find support for age influencing both the relationship between PU and intention and PU and attitude. Tarhini *et al.* (2014) stipulates that age moderates the effect of PU on the intention to accept e-learning systems. Similarly, Al-Gahtani (2010) determine that age moderates the relationship between PU and attitude and also the relationship between PU and intention. Tarhini *et al.* (2014) find that age moderates the effect of PU on BI. Finally in an agricultural context, Rübcke von Veltheim *et al.* (2021) find that age has a moderating influence on the relationship between PU and intention. This leads to the following hypotheses:

H_{8a} : The relationship between Perceived Usefulness and the Behavioural Intention to adopt SFT is moderated by Age.

H_{8b} : The relationship between Attitude and the Behavioural Intention to adopt SFT is moderated by Age.

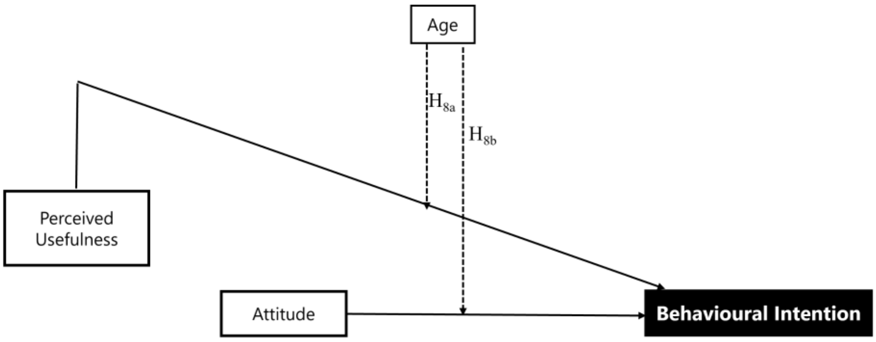

Figure 3.9 Hypothesis Eight

3.3.7.3 Education

Education is important in encouraging farmers to adopt SFT, as outlined by several authors (Barnes *et al.*, 2019b; Daberkow and McBride, 2003; Das *et al.*, 2019; Vecchio *et al.*, 2020). Adrian *et al.* (2005) find that increased education levels positively impact the intention to adopt agricultural technologies. In the context of internet banking, Abu-Shanab (2011) find that education moderates the relationship between performance expectancy and intention. Similarly, Owusu Kwateng *et al.* (2019) deduce that education acts as a moderator between performance expectancy and intention in their study of mobile banking in Ghana. In addition, AlHadid *et al.* (2022) find that education level has a moderating effect on attitude. However, the moderating role of education has largely been ignored by several behavioural models (Li *et al.*, 2014). As a result, the following hypotheses are proposed:

H_{9a} : The relationship between Perceived Usefulness and the Behavioural Intention to adopt SFT is moderated by Education.

H_{9b}: The relationship between Attitude and the Behavioural Intention to adopt SFT is moderated by Education.

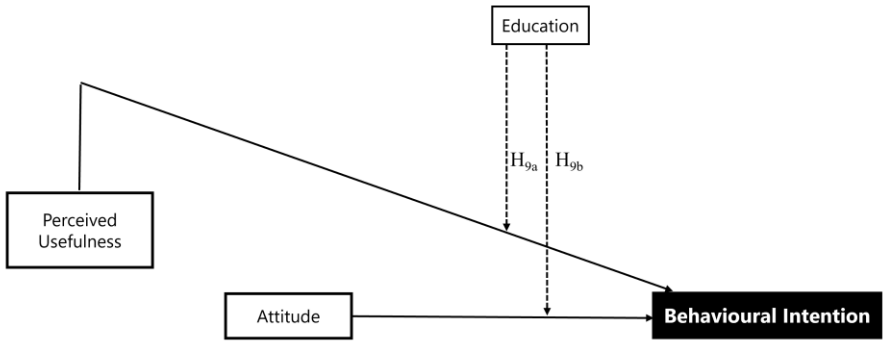

Figure 3.10 Hypothesis Nine

3.3.7.4 Farm Size

As discussed in Section 2.5.2.1, farm size has a significant influence on technology adoption decisions. Adrian *et al.* (2005) deduce that farm size affects the intention to adopt agricultural technologies. Similarly, it is stipulated that farmers with a larger land mass are more likely to consider adopting SFT (Rossi Borges *et al.*, 2019). Giua *et al.* (2022) find that the size of the farm has a positive relationship with the adoption of SFT. Larger scale farms are more likely to adopt SFT due to economies of scale and the ability to invest (Aubert *et al.*, 2012; Castle *et al.*, 2016; Tey and Brindal, 2012). However, Jayashankar *et al.* (2018) and Pillai and Sivathanu (2020) determine that farm size has no influence on the intention to adopt smart technology in an agricultural context. Both these studies used farm size as a control variable rather than a moderator. However, farm size has also been used as a moderator. Schukat and Heise (2021a) propose that farm size has a moderating effect on the relationship between facilitating conditions and BI and technology readiness and BI. Téllez *et al.* (2021) used farm size as a moderator in their study of farmers' participation in conservation practices. They find that farm size moderates the relationship between interest in the programme and participation.

This leads to the following hypotheses.

H_{10a} : The relationship between Perceived Usefulness and the Behavioural Intention to adopt SFT is moderated by Farm Size.

H_{10b} :The relationship between Attitude and the Behavioural Intention to adopt SFT is moderated by Farm Size.

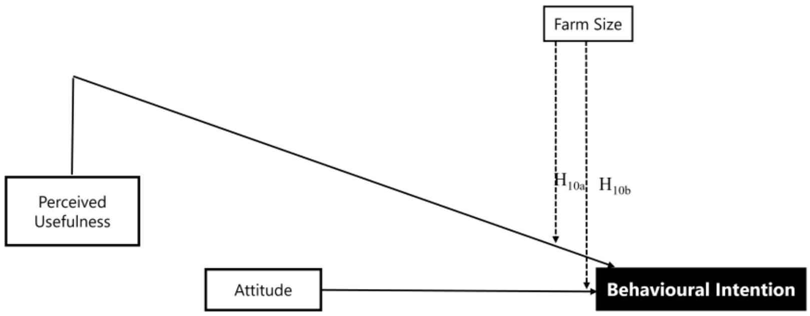

Figure 3.11 Hypothesis Ten

3.4 Control Variable

Control variables are used in research to determine the causal effect of the variable on the dependent variable (Hünermund *et al.*, 2022). As outlined in Section 2,4, non-adopters and adopters of SFT are likely to have different perceptions and attitudes towards using the technology (Kernecker *et al.*, 2019). Therefore, SFT experience is added as a control variable in the model.

3.5 Conclusion

In this chapter a conceptual model and the related detailed hypotheses were developed to address the overall research question. Both the hypotheses and components of the integrated model were developed from the extant literature, particularly related to TAM. The literature suggests that an individual's behavioural intention (BI) to adopt SFT is based on their attitude towards using the technology. The BI is also directly influenced by the Perceived Usefulness (PU) of the technology. Attitude towards using the technology is formed based on the farmer's perception of the usefulness and ease of use (PEOU) of the technology. Thus, attitude mediates the relationship between BI and PEOU and PU. Furthermore, it is posited that Trust in the SFT vendor has a direct influence on the farmer's attitude towards using SFT. This trust is influenced by the PEOU of SFT and subsequently influences the PU of the technology. Additionally, Personal Innovativeness in IT as a personality trait influences both the PU and PEOU of SFT. Finally, the PU of SFT is impacted by Social Influence. The final hypothesised model for this study is outlined in Figure 3.12.

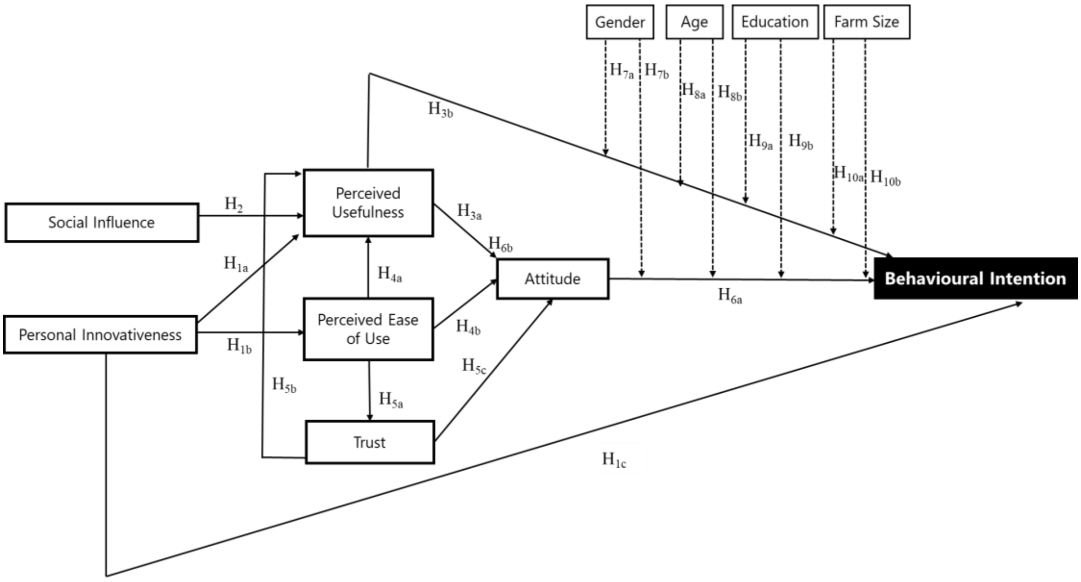

Figure 3.12 Final Conceptual Model

Chapter 4: Research Design and Methodology

4.1 Introduction

The previous chapter presented the proposed conceptual model and related hypotheses, based on the extant literature. This chapter outlines the methodological approach to the research. It presents the philosophical foundation of the research, the research design, and the chosen research method to address the overall research question. Section 4.2 presents an overview of the main philosophical assumptions and approaches associated with research and details the researcher's chosen philosophical approach. Section 4.3 explains the research design and justifies the researcher's chosen methods. Section 4.4 outlines the questionnaire development process which includes conceptualisation and operationalisation of the constructs, alongside pilot testing and data collection methods. Finally, Section 4.5 details the data analysis plan to ensure reliability and validity of the data. Structural equation modelling (SEM) is presented as the multivariate statistical analysis technique to analyse the hypothesised relationships.

4.2 Philosophical Assumptions

Before research can be conducted, Guba and Lincoln (1994) determine that three aspects must be addressed: the philosophical stance of the researcher regarding ontology and epistemology, and the broad methodology and methods of research being undertaken. The research paradigm, which is defined as a set of beliefs providing theoretical frameworks regarding how problems should be understood and addressed (Kuhn, 1962), encompasses these three outlined dimensions (Terre Blanche and Durrheim, 1999). Consequently, the researcher's perspective on science and society determines their assumptions regarding ontology, epistemology, and human nature (Burrell and Morgan, 1979; Crotty, 1998; Easterby-Smith *et al.*, 2008). Understanding of the various philosophical assumptions allows the researcher to develop greater self-awareness and reflection on data and its multiple perspectives (Gummesson, 2003). This understanding also shapes how the research problem and research objectives are formulated (Huff, 2009). Five specific research paradigms generally exist: positivism, post positivism, social constructivism/interpretivism, critical theory and pragmatism (Easterby-Smith *et al.*, 2008; Guba and Lincoln, 2005; Lincoln *et al.*, 2011; Nyein *et al.*, 2020). Each paradigm is based on its own assumptions related to ontology and epistemology (Scotland, 2012). An explanation of the various research paradigms and their associated philosophical underpinnings is thus presented.

4.2.1 Research Paradigms and Approaches

Positivism assumes that there is a reality which can be studied objectively (Guba and Lincoln, 2005). Saunders *et al.* (2012) explain that with a positivistic approach the researcher is separate from reality, thus resulting in more objective data, less subject to bias. Reliability, validity and the use of large data sets to infer generalisability are important for the positivist researcher (Park *et al.*, 2020) A structured methodology using scientific methods is followed to enable replication (Kumar, 2014). Such scientific methods allow for experimentation, objectivity and control (Asghar, 2013). This is consistent with a deductive approach to research where theory is examined and hypotheses created, followed by operationalisation and experimentation (Park *et al.*, 2020). However, Hammersley (2013) and Popper (1983) identify several concerns related to positivism, namely the difficulty in measuring complex phenomena which cannot be observed and the need for perfect conditions to test hypotheses and conduct experiments. Furthermore, Fox (2008) argues that positivism ignores context. As a result, post-positivism emerged which has similar ontological and epistemological underpinnings to positivism, but differs in the assumption that reality can only be approximated (Guba, 1990) and therefore verification of theories is important (Wilson and Vlosky, 1997). Fox (2008) explains that understanding and learning is more important than explanation and testing to the post positivist researcher. Reflexivity is central to post-positivism (Ryan, 2006). Consequently, the paradigm recognises that cause and effect in research is probable but not always guaranteed, therefore multiple perspectives exist rather than a single reality (Creswell and Poth, 2018). However, Avenier and Thomas (2015) highlight a weakness in post-positivism for primarily still using statistical techniques to address complex realities. Kirby (2013) also explains that generally post-positivists believe that the problem of inductive generalisation exists within the paradigm which is difficult to address.

Social constructivism, which is also used interchangeably with interpretivism, believes that there is no objective reality, instead reality is subjective and socially constructed (Schwandt, 1994). Knowledge is created by individuals and is shared through their interactions with researchers (Racher and Robinson, 2003), thus allowing investigation of complex phenomena. As such, multiple realities exist (Rehman and Alharthi, 2016), with the researcher making observations based on their experiences, resulting in a gap between the data collected and its reality (Blaikie and Priest, 2019). Grix (2004) explains that interpretivists try to understand social phenomena rather than discover it. The paradigm emerged from the philosophy of phenomenology, founded on the inability of positivistic research to deliver insights into the complex social world (Mertens, 2019). Qualitative methodologies are therefore mostly used to allow the individual to share their experiences (Scotland, 2012). An inductive approach is adopted, developing theories based on observations from the data (Grix, 2004). Interpretivism has been criticised, mainly due to its lack of generalisability and lack of objectivity (Cohen *et al.*, 2007). Furthermore, deriving a conclusion can be problematic due to reality being subjective (Rolfe, 2006).

Critical theory or the transformative paradigm sees reality as being shaped by domination (power relations) and alienation (social struggles) in society and, therefore, should be viewed through these existing structures (Morrow and Brown, 1994). Power relations associated with social and cultural aspects such as gender, race, religion and education all impact this reality and therefore the researcher must consider this (Bronner, 2011). Social oppression is, therefore, acknowledged and addressed (Kellner, 1990). Mertens (2019) outline that four characteristics distinguish the transformative paradigm from positivists and interpretivists. First, diverse groups which have been previously marginalised are central to the research. Next, understanding why inequalities exist in society based on race, culture, gender, disability, sexual orientation etc. is explored. Third, it examines how political and social action result in inequalities. Finally, transformative theory has as a key goal the development of research programmes. Critical theorists posit that the object being researched is affected by the researcher, therefore a duty of care lies with the researcher to be conscious of their epistemological beliefs (Rehman and Alharthi, 2016). Thus, a collaborative approach is needed between the researcher and the subjects to prevent marginalisation (Guba and Lincoln, 1994). Flexibility in research methodologies and methods is important allowing the researcher to answer the research question adeptly (Asghar, 2013). The primary critique of critical theory lies in the failure to provide standards which demonstrate superiority over other paradigms (Gibson, 1986). Furthermore, the paradigm is also criticised for its slowness in enacting change due to the research being focused on multifaceted social and political structures (Jahn, 2021).

Pragmatism argues that more than one philosophy can be adopted within a research project to allow the researcher to achieve the defined objectives (Ragab and Arisha, 2017). It rejects the idea that research is either subjective or objective (Biesta, 2010) and believes that answering the research question is more important than the research methods or theory used (Tashakkori and Teddlie, 2008). Thus, pragmatists believe in both positivist and interpretivist associations and subsequently tend to adopt a mixed methods research approach (Saunders *et al.*, 2012). Importance is placed on the practicality of research, rather than the philosophical arguments regarding reality and knowledge (Morgan, 2014). However, Holden and Lynch (2004) question the pragmatic approach, arguing that the researcher should have a chosen ontological and epistemological stance to allow them to choose methods to answer the research question. Each of the paradigm's views on ontology, epistemology, and methodology are discussed further below.

4.2.2 Ontology

When determining the philosophical approach, the researcher's view of ontology, or the nature of reality, must firstly be examined (Holden and Lynch, 2004). Ontology is concerned with whether theories represent reality and processes outside the human mind or whether they comprise explanations that are thought of to guide research (Kilduff *et al.*, 2011). Intrinsically, ontology is primarily concerned with the nature of existence. The objectivist approach to social science, otherwise known as realism, believes that objects exist independently of the individual researcher (Cohen *et al.*, 2007). It explains relationships and identifies the causes which determine outcomes (Creswell, 2009). The positivist approach to research is therefore concerned with realism (Frowe, 2003), while post-positivism has a critical realist ontology (Kirby, 2013). The nominalist or subjective approach to social science views reality as differing from person to person (Guba and Lincoln, 1994) and therefore multiple realities exist (Scotland, 2012). This approach, also known as constructionism, is concerned with the interpretivism paradigm, detailing that reality only emerges when there is engagement with objects who already have meaning (Crotty, 1998). Critical theorists also recognise that multiple versions of reality exist, but that it is shaped by society (Bronner, 2011). Pragmatists are not overly concerned with the definition of reality but instead believe there is a single reality and individuals have a subjective view of that reality (Mertens, 2019). Most of the social science research is based on the assumption that reality is objective, and the related knowledge can be identified and relayed to other individuals (Holden and Lynch, 2004).

4.2.3 Epistemology

Epistemology is concerned with how an individual accesses knowledge and the relationship between knowledge and truth (Kilduff *et al.*, 2011). Essentially, it is the researcher's way of looking at the world and how they make sense of it (Al-Ababneh, 2020). Usunier (1998) outlines how fundamentally two philosophies of epistemology exist: positivism and interpretivism. Hasan (2014) stipulates that positivists are concerned with meaningful statements which are given scientific consideration. The positivist approach to epistemology is through objectivism, or impartially discovering knowledge (Scotland, 2012). Similarly, Guba and Lincoln (2005) note that the positivist's view of epistemology is objectivist, where findings are acknowledged as true. Thus, positivists have an objective view of knowledge, viewing the researcher and the research as separate and discovering knowledge impartially (Crotty, 1998). August Comte, who first introduced the concept of positivism, explains that it is an approach that specifies truths through empirical observation (Babbie, 2014). Positivism is therefore based on "*empirical social science methods, and broadly these use four tests of validity. These four tests are construct validity, internal validity, external validity and reliability*" (Quinton and Smallbone, 2005, p. 301). Consequently, positivism is concerned with cause and effect and seeks generalisation (Gill and Johnson, 2002). Post-positivism shares similar underpinnings on epistemology, but stipulates that the researcher's biases, knowledge and hypotheses can shape the nature of their observations (Mertens, 2019). Crotty (1998) further explains that post-positivists argue that understanding theories requires more than empirical data, thus placing importance on using qualitative techniques also.

Interpretivism or subjectivism is concerned with trustworthiness and authenticity (Adcroft and Willis, 2008) and believes that human action shapes the world (Gill and Johnson, 2002). Interpretivists have a subjective view of knowledge, considering that the world does not exist without the individual's knowledge of it (Grix, 2004). Qualitative data methods are important to therefore build knowledge (Kelliher, 2005). Thus, in research, knowledge is obtained through the researcher interacting with the human subjects of interest (Walsham, 1995). In the critical theory or transformative paradigm, knowledge is constructed in the context of political and social issues (Mertens, 2019). Alternatively, pragmatists generally believe that knowledge is socially constructed, but varies according to individuals' experiences (Morgan, 2014). The subsequent critique of interpretivism is lack of generalisability and validity and reliability issues (Perry, 1998).

Singh (2015) stipulates that there is a clear divide between positivism and interpretivism, therefore it is essential that the researcher selects one approach and states it clearly. Positivism, although challenged, is still the dominant public model for research (Hasan, 2014). Table 4.1 summarises the elements which define and differentiate positivism and interpretivism.

Table 4.1 Contrasting implications of Positivism and Interpretivism

	Positivism	Interpretivism
The observer	Must be independent	Is part of what is being observed
Human Interests	Should be irrelevant	Are the main drivers of science
Explanations	Must demonstrate causality	Aim to increase general understanding of the situation
Research progresses	Hypotheses and deductions	Gathering rich data from which ideas are induced
Concepts	Need to be operationalised so that they can be measured	Should incorporate stakeholder perspectives
Units of Analysis	Should be reduced to simplest terms	May include the complexity of 'whole' situations
Generalisation through	Statistical probability	Theoretical abstraction
Sampling requires	Large numbers selected randomly	Small numbers of cases randomly chosen for specific reasons

Source: Adopted from Easterby-Smith *et al.* (2008)

4.2.4 Human Nature

The third philosophical assumption relates to human nature and whether the researcher views man as the controller or as the controlled (Burrell and Morgan, 1979). The objective view, also known as determinism, assumes that causal laws that operate within the nature of society are predicated based on previous events that have happened (Mills, 2013). As such, determinism is defined as "*the view that every event has a cause….All things in the universe are 'governed' by or operate in accordance with causal laws*" (Angeles, 1981, p. 60). This view sees humankind being determined by the situation and the environment. Thompson *et al.* (1989) state that a positivistic approach to research assumes that human nature is governed and therefore deterministic. The opposing or subjective view, known as voluntarism, believes in free will and autonomy, and the capacity of individuals to control their behaviour by making choices based on self-determined motives and intentions (Hanaan and Radhakrishna, 2015).

4.2.5 The Researcher's Philosophical Approach

There is no correct philosophical approach, instead the researcher's philosophical assumptions leads them to conduct research in a particular way (Johnson and Duberley, 2000). Understanding the differences in paradigms allows the researcher to assess the suitability of their research methodology in answering the research question, and opens the researcher's mind to new possibilities (Holden and Lynch, 2004). This study adopts an objective realist, ontological stance. The belief is that individuals, or farmers in this context, make their decisions in an objective and observable reality, existing independently of the researcher's perceptions. The researcher's ontological assumption is that several factors influence the farmer's behavioural intention to adopt SFT, irrespective of whether or not the researcher investigates the phenomenon.

The epistemological stance of positivism is adopted, determining that new knowledge can be acquired through examining preceding evidence (Burrell and Morgan, 1979). This positivistic approach searches for explanations that fit with reality and aims to discover patterns which can be statistically assessed. The researcher believes that the investigator is independent from the study, supporting the view of positivism as outlined by Hammersley (2013). As detailed by Fisher (2010), positivistic research delivers unbiased knowledge related to humans and their behaviour. The researcher believes that knowledge, related to farmers' intentions to adopt SFT can be obtained through objective and empirical methods. Furthermore, the goal of this research is to develop a model which explains the factors influencing the farmer's behavioural intention to adopt SFT, thus a positivistic, deductive approach is deemed appropriate. This deductive approach draws on previously specified conceptual relationships and theoretical frameworks to derive and subsequently test hypotheses. These hypotheses must be conceptualised in such a way that facilitates facts to be measured quantitatively (Creswell and Creswell, 2018). Quantitative methods of inquiry are thus deployed, as detailed in Section 4.2.6, to empirically test the relationships between the key variables conceptualised in Chapter 3. A deterministic approach of human nature is considered for this research, with the view that farmers' behaviour is primarily determined by external factors, and they have relatively little control over their destiny.

The researcher was embedded in the DEMETER project which funded this research, in a marketing capacity. Thus, this positivistic, deductive approach using quantitative techniques also helped to further minimise any potential funding bias and researcher confirmation bias.

4.2.6 Research Methodologies

The aim of the methodology is to identify the appropriate data collection techniques to allow the researcher to study the established topic (Fisher, 2010). The researcher's ontological and epistemological assumptions are reflected in their chosen methodological approach (Grix, 2004). Newman and Benz (1998) deduce that a qualitative or quantitative research approach can be taken, although these approaches should not be viewed as opposites but instead as ends of a continuum. Furthermore, a mixed methods approach, combining qualitative and quantitative elements, has become increasingly used by researchers (Creswell, 2009). Consequently, an outline of a quantitative research approach and its associated methods is provided, along with a discussion of its advantages and challenges. Next, an overview of qualitative methods and their associated benefits and disadvantages is discussed. A review of mixed methods research is then provided. Finally, the rationale for the researcher's methodological approach is outlined.

4.2.6.1 Quantitative Methods

A positivistic approach is usually associated with quantitative methods (Wildemuth, 1993) to deliver a measured understanding of phenomena (Hammersley, 2013). Post-positivists also predominately use quantitative methods but understand that qualitative techniques can be needed to understand complex situations (Mertens, 2019). Quantitative research is described as the process of analysing the theory behind concepts and subsequently developing hypotheses to test the theory (Bryman, 2012). Such an objective approach is expected to lead to more generalisable findings (Hair *et al.*, 2019c). Deductive reasoning is applied where the research is conducted using hypotheses gathered from theory (Bryman, 2012). It moves from the general to the specific, starting with the "why" and moving to "whether" (Babbie, 2014). Quantitative techniques allow the researcher to then formulate a conclusion (Stake, 1995), which is delivered through analysing numerical data captured from a sample of respondents (Choy, 2014). Methods include surveys, simulation, field experiments, correlation studies or multivariate analysis (Queirós *et al.*, 2017). Stockemer (2019) outlines that surveys are one of the most used quantitative methods with results helping to shape political and social sciences. Surveys can be administered through the internet, through post or over the phone and can be self-completed or delivered through the use of an interviewer (Meadows, 2003). Furthermore, cross-sectional surveys gather consensus from individuals at a moment in time, while longitudinal surveys repeat the survey multiple times to ascertain changes in trends

(Rahman, 2016). The use of surveys with a large sample provides a high level of reliability and validity (Cohen *et al.*, 2007) and delivers an objective approach enabling generalisation (Creswell, 2014).

The benefits associated with a deductive, quantitative approach relate to a quicker turnaround time to conduct the research and analyse the data (Creswell and Creswell, 2018). The researcher is deemed independent or objective of what is being researched (Saunders *et al.*, 2012). This can lead to results being generalised to a wider population, provided the sample is representative of the population (Bryman and Bell, 2011). Furthermore, it is a more appropriate approach when the researcher seeks to understand and explain the relationship between variables (Mertler, 2016). However, limitations also exist with a quantitative approach. Bryman (2012) outlines how the researcher can be unclear, when using a survey, whether the respondent is answering the question truthfully or is indeed interpreting the question correctly. Equally, the respondent does not have the opportunity to explain their answers, resulting in a limited understanding of why a phenomenon occurs (Rahman, 2016). Creswell and Creswell (2018) also explain that a major disadvantage of quantitative research is its non-flexibility, with the researcher following a set approach and using a set of pre-determined questions. This may result in a lack of critical and creative thinking from the researcher (Shank and Brown, 2007). Finally, Queirós *et al.* (2017) outline further limitations of quantitative research relating to the data analysis process and the use of statistical significance tests which may not be robust.

4.2.6.2 Qualitative Methods

An interpretivist approach uses qualitative data and relies on methods such as interviews, focus groups and analysing existing text (Lin, 1998). As such, qualitative research refers to the subjective exploring and understanding of a phenomenon through analysing text and images as opposed to numbers or statistics (Flick, 2014). The interpretivist believes these approaches are necessary as phenomena need to be understood "*through the eyes of the participants rather than the researcher*" (Cohen *et al.*, 2007, p. 21). Thus, human information offers meaning, according to the interpretivist thinking (Saunders *et al.*, 2012), tying in with the ontological stance of reality being socially constructed (Lincoln *et al.*, 2011). This leads Guba and Lincoln (1994) to determine qualitative approaches to research as being more natural. Overall, an inductive approach is applied, drawing conclusions by identifying themes that result in new theory or refined theories (Creswell, 2014).

Through the use of interviews, focus groups, direct observations, field research and ethnographic approaches, detailed data can be obtained relating to the respondents and their attitudes, experiences, behaviours and beliefs (Queirós *et al.*, 2017). Surveys can also be adopted as a qualitative tool, by using a series of open-ended questions, although their use in qualitative research has been limited (Braun *et al.*, 2020). Overall, such qualitative methods offer a deeper understanding and richer interpretation of respondent's thoughts and feelings compared to quantitative techniques (Rahman, 2016). The approach is more flexible leading to a more in-depth assessment of complex phenomena (Flick, 2014). Thus, qualitative methods allow for theory-building and the unveiling of new concepts (Stockemer, 2019).

Disadvantages associated with qualitative techniques include the time associated with conducting the research, data interpretation and data analysis (Flick, 2014). Due to the non-standardised nature of qualitative data, it most likely needs to be condensed and categorised to find trends and present the results meaningfully (Saunders *et al.*, 2012). In addition, due to generally smaller sample sizes and the inability to generalise findings, it can be difficult to draw conclusions and consequently results can have low credibility (Queirós *et al.*, 2017). However, understanding and addressing the subjectivity and reflexivity of the researcher can help to offset some of the criticisms associated with qualitative research (Braun *et al.*, 2017).

As outlined, the interpretivist approach favours qualitative methods. Conversely, the critical theory approach to methodology varies, with some researchers focusing on quantitative methods but recognising that care is needed to avoid biased results (Mertens, 2008). Other researchers from this paradigm believe that qualitative methods or mixed methods are required to facilitate engagement with participants and allow them to receive meaningful benefits from the research (Creswell, 2009). Thus, mixed methods research is discussed in more detail below.

4.2.6.3 Mixed Methods

A mixed methods approach to research involves combining an element of qualitative and quantitative research and data to answer the research question (Creswell, 2014). This refers to combining numerical data from surveys or structured observations with non-numerical data from techniques such as interviews or focus groups or vice versa (Saunders *et al.*, 2012). Such an approach to research addresses the shortcomings of solely following a quantitative or qualitative approach (Kelle, 2015). Shan (2021) however determines that there is no consensus on the philosophical assumptions which underpin a mixed methods approach. Pragmatism is most often associated with mixed methods, using qualitative and/or quantitative methods, based on their appropriateness to answer the research question (Morgan, 2014). Similarly, Tashakkori and Teddlie (2008) determine with a mixed methods approach, the researcher is not preoccupied with truth and reality, but instead focuses on answering the research question appropriately.

Schoonenboom and Johnson (2017) outline how mixed methods can be used to examine multiple aspects of one research question or to address separate but related questions. However, the qualitative and quantitative data needs to be integrated at some point to provide a richer understanding of the research problem (Zhang and Creswell, 2013). Three strategies can be followed for a mixed methods approach: sequential, concurrent and transformative (Creswell and Creswell, 2018). Sequential mixed methods research starts with one research approach and then adds a second approach to either generalise or explore the findings (ibid). Concurrent mixed methods occurs where the qualitative and quantitative element are carried out simultaneously, while transformative mixed methods is when the researcher uses a theoretical lens to assess qualitative and quantitative data. Regardless of the mixed methods approach used, clear justification is needed, outlining the rationale, the associated philosophy of combining methods, the method of integrating data and demonstration of rigour (Creswell, 2009).

The major advantage of mixed methods research is the broader depth of understanding associated with its undertaking (McKim, 2016; Schoonenboom and Johnson, 2017). Combining deductive and inductive perspectives allows the researcher to generate theory and also test hypotheses in one single study (Jogulu and Pansiri, 2011). Alongside this, increased credibility and validity is a notable positive, strengthening the research conclusion through the process of triangulation which cross-verifies the findings (Saunders *et al.*, 2012; Tashakkori and Teddlie, 2008). In opposition, as more than one research method is being employed, the time to conduct the research can increase significantly (Halcomb and Andrew, 2009). Integrating the data can also be problematic and difficult to achieve (Bryman, 2012). Furthermore, the implications of resources and cost can be an issue (Creswell, 2014), while the researcher must also have appropriate quantitative and qualitative skills (McKim, 2016). Shang *et al.* (2021) further outlines that justifying the use of a mixed methods approach can be controversial from a philosophical point of view.

4.2.6.4 The Researcher's Quantitative Research Methodology

Considering the overall research question to examine the factors influencing farmers' intentions to adopt SFT, a quantitative, qualitative or indeed mixed methods approach could have been followed. Through the use of interviews or focus groups, an in-depth understanding of farmers' experiences of adopting or choosing not to adopt SFT would have been possible. Similarly, combining interviews with a survey would have allowed for a thorough exploration of farmers' intentions and behaviours. However, as one of the main objectives of the research was to understand the relationship between variables and to build a model to explain the factors which influence farmers' behavioural intentions to adopt SFT, a quantitative approach was deemed more suitable. Additionally, as the researcher was working in the project which funded the research, it is considered that a quantitative approach would also ensure further objectivity. The use of a survey would provide a structured, objective, and statistically robust means of examining the factors influencing farmers' intentions to adopt SFT, somewhat mitigating potential biases and enhancing credibility.

Furthermore, the researcher's philosophical assumptions should underpin the selection of the methodology (Creswell and Creswell, 2018). As outlined in Section 4.2.5, the researcher identifies with the positivist paradigm taking an ontological stance of realism and an epistemological perspective of objectivism. With the positivist paradigm, Baškarada and Koronios (2018) explain that nomological prediction and explanation is the main aim. This essentially means that the research should be based on pre-existing theory which specifies the relationships between constructs. Consistent with a deductive approach, this research uses the Technology Acceptance Model (TAM), as outlined in Chapter 2, as its main theoretical lens. Thus, using a quantitative approach aligns with the goals of TAM to understand technology adoption behaviour through empirical research (Marangunić and Granić, 2014). In addition, generalising the results to a larger population of farmers was a key driver for the research, again justifying the selection of a quantitative approach. This therefore led to the employment of a web-based, structured questionnaire as the chosen data collection method. Saunders *et al.* (2012) outlines how such surveys enable the collection of data from a sizeable population across several locations, allowing for descriptive and inferential analysis. However, Wright (2017) determines the disadvantages of a web-survey relate to the design of the survey, sampling issues, self-selection bias, and access issues. Having a clear research design is thus important to offset the associated disadvantages of web-based surveys. Further detail on the research design followed in provided in Section 4.3.

4.3 Research Design

The research design outlines the framework employed to collect and analyse data and allows the researcher to address the predefined research objectives (Bryman and Bell, 2011; Hair *et al.*, 2003). It focuses on the research strategy, research choices and time horizons (Saunders *et al.*, 2012). As previously outlined, the researcher's philosophical assumptions influence their research approach and subsequent research design and methods (Johnson and Clark, 2006). Coursey (1989) determine that three assumptions must be examined before selecting the research design and method: context, causality, and generalisation. There is a trade-off between each assumption, therefore the researcher must select the appropriate research method(s) that align with their motivations for conducting the research. The researcher adopts a positivistic research philosophy, determining that knowledge is obtained through observation and measurement. Thus, as outlined, quantitative techniques are adopted in this study to provide empirical evidence of the factors influencing farmers' behavioural intention to adopt SFT. Furthermore, as the research was conducted during and following the Covid-19 pandemic, the use of an online survey allowed access to respondents.

The research design can be either experimental or non-experimental. Experimental design focuses on experimental research methods which use a randomised control or comparison group against the sample of interest for the research (Blundell and Costa Dias, 2005). The variable(s) of interest can be controlled or manipulated by the researcher to determine its effect on the dependent variable (Shadish *et al.*, 2002). The internal and external validity of experimental data is maximised (Rogers and Révész, 2020; Walker, 2016), thus leading to experimental research being established as a superior method of research and data collection (Reio, 2016). Although the information provided is valuable, experimental design can be difficult to implement due to logistical issues such as cost and time, as well as ethical issues (Cook and Cook, 2008; Falkenstrom *et al.*, 2023). Furthermore, Walker (2016) lists sampling issues and reductionism as disadvantages of experimental research. Ballance (2023) asserts that larger sample sizes and longitudinal studies are needed with experimental studies to provide generalisable results. Therefore, although an experimental design would be feasible for this study, it was considered impractical to address the research question within a suitable timeframe. Furthermore, as there are several independent variables in the proposed, integrated model which have a relationship with the dependent variable, it would be difficult to control and manipulate each of these variables accordingly.

Conversely, non-experimental research designs are commonly used in social science research, using methods such as interviews, content analysis, questionnaires, focus groups and surveys (Reio, 2016). They are generally seen as weaker at determining causality (Cook and Cook, 2008) and more prone to bias (Thompson and Panacek, 2007). Indeed, a study from Omotilewa and Ricker-Gilbert (2019) compared experimental estimates to non-experimental estimates to evaluate the role of extension agents in agricultural technology adoption. The researchers found that overestimation was present in non-experimental studies, thus suggesting bias may be evident. However, they also note that bias occurs in experimental estimates. With non-experimental design, there is no manipulation of variables, rather the researcher focuses on the relationships between variables (Reio, 2016). Non-experimental design is often used if, a) causal relations are not involved in the questions of interest, b) the variables of interest cannot be manipulated, and c) the use of non-experimental measures increases the overall efficiency of the research and how quickly it can be conducted (Wegener and Fabrigar, 2000). Consequently, a non-experimental research design is followed. Kerlinger (1986) argues that determining the relationships between variables is more important than experimental research, as establishing the link between variables must be understood before the effect can be decided. Furthermore, Bonds-Raacke and Raacke (2014) state that non-experimental research is important in advancing a particular field of study.

Non-experimental studies are more practical to conduct (Kirk, 2013). Ogundari and Bolarinwa (2018) determine that most studies examining agricultural technology adoption are non-experimental or observational. Therefore, as there are several variables of interest in this research and due to constraints of resources, a non-experimental research design was adopted. Moreover, the research required a sample of farmers to determine the key factors which influence their behavioural intention to adopt SFT. Consequently, a cross-sectional study using a survey was deemed an appropriate method of data collection. Cross-sectional studies analyse data from the population of interest at a single point in time. and are often used to understand behaviours (Hair *et al.*, 2003; Wang and Cheng, 2020). Doss (2006) determines that such cross-sectional studies are useful when examining technology adoption and farmer preferences and perceptions. Spector (2019) acknowledges that cross-sectional studies are often criticised due to the inability to draw causal inferences and also the possibility of common method variance. However, he notes that such methods are efficient and suitable in new contexts and if a timeframe for a longitudinal study cannot be established. Furthermore, Wunsch *et al.* (2010) note that causal inferences can be obtained with cross-sectional studies when structural modelling is used. Taris *et al.* (2021) deduce that cross-sectional studies are therefore suitable for testing assumptions regarding the variables of interest.

4.3.1 Causal Research

Research can be exploratory, descriptive or causal in nature (Saunders *et al.*, 2012). Causal Research, also known as explanatory research, determines causal inferences and allows the researcher to draw conclusions based on the data and theoretical assumptions (Pribesh and Gregory, 2018). Structural equation modelling (SEM), as a form of statistical analysis, enables the determination of such causal inferences (Hair *et al.*, 2017a). SEM is "*a statistical methodology that takes a confirmatory (i.e., hypothesis-testing) approach to the analysis of a structural theory bearing on some phenomenon*" (Byrne, 2010, p. 3). It represents causal processes that are characterised by structural equations which, in turn, help to develop a model to represent the theory being examined (Byrne, 2010). SEM is therefore used to establish causality which indicates a relationship between variables (Mulaik and James, 1995). Hair *et al*., (2010) outline that four established criteria are necessary to establish causality; 1) association or covariance between two variables, 2) correct ordering of the variables under investigation to determine cause and effect otherwise known as directionality, 3) no other reasonable causes for the outcome being present (isolation), and 4) theoretical support for the hypothesised relationships based on several studies. Association refers to the fact that cause and effect must be related (Bollen, 1989b). Directionality concerns the direction of the relationship which is based on theory, research design or logic (Hoyle, 1995). Isolation relates to the assumed cause being isolated from other causes (ibid). Using SEM to conduct causal analysis enables the examination of complex social phenomenon (Tarka, 2018). This research examines theoretical constructs such as social influence, perceptions, attitudes, and behavioural intention. Consequently, SEM is deemed a suitable approach and is detailed in Section 4.5.

The use of survey methods for data collection is a prevalent approach for cross-sectional studies that use a non-experimental design approach (Easterby-Smith *et al.*, 2008; Saunders *et al.*, 2012). It is consistent with the positivistic perspective of using quantitative methods that deliver an objective approach (Bryman, 2012; Creswell and Creswell, 2018). Surveys can use many collections methods such as questionnaires and interviews (Dillman *et al.*, 2014) and incorporate email, post, face to face and telephone, as a means to gather the data (Hair *et al.*, 2003). They are recognised as an efficient method of gathering data from a wider population and allow the implementation of many methods of instrumentation (Walliman, 2011). Additionally, they are useful to gather data regarding attitudes and behaviour (Bonds-Raacke and Raacke, 2014). A self-administered, web-based questionnaire was used in this research as it was an efficient method of reaching a wide range of farmers across different farming contexts. Web-based questionnaires offer several advantages such as access to participants, economy of design, lower cost of implementation, shorter administrative procedures, and effective data analysis methods (Evans and Mathur, 2005; Queirós *et al.*, 2017). They enable the identification of attributes from a small group of individuals to a larger cohort or population (Fowler, 2002). However, such surveys are not without their limitations. Participants who do not have access to the internet are ignored, which could potentially lead to bias (Bethlehem, 2010; Fan and Yan, 2010). Respondents can also be distracted, unmotivated and unsure of the correct procedures to complete the survey (Pokropek *et al.*, 2023). Therefore, it is critical that researchers take sufficient time to assess the questionnaire design, development, evaluation, and testing (Beatty *et al.*, 2019). This is discussed in more detail in Section 4.4.

With the researcher's philosophical assumptions and chosen research methodologies determined, ethical approval was sought and subsequently approved by South East Technological University (SETU), allowing the researcher to proceed with the research.

4.4 Questionnaire Development Process

Survey research requires strong survey design, validation through pretesting and good survey administration to enable robust data collection (Hair *et al.*, 2003). Furthermore, when developing the questionnaire, Singh (2017) stipulates that it is important that the population of interest is considered, as this influences the wording of questions and subsequent flow. In this research, farmers are the population of interest, therefore attention was paid to ensure that the language used was familiar and easily understood. A strong understanding of the research problem and objectives is essential, guided by the theoretical framework adopted by the research (Bryman, 2007). This is facilitated by the literature review as detailed in Chapter 2. The next step is conceptualisation and operationalisation of the constructs and questions to be used in the questionnaire (Saunders *et al.*, 2007). Question type and order should also be considered (Dillman *et al.*, 2014). Each of these elements are now discussed in more detail.

4.4.1 Qualitative Interviews to guide questionnaire development

As suggested by Gillham (2007), semi-structured interviews with the audience of interest can help to guide the development of a questionnaire. Such interviews can, in particular, assist with the development of measurement items and hypotheses in the early stages of research (Churchill, 1979; Rotchanakitumnuai and Speece, 2003; Willis, 2015). Therefore, eight interviews were conducted with farmers to help develop the questionnaire. This process enabled the researcher to clarify concepts and to gain further understanding of the influences on the farmer's behavioural intention to adopt SFT. An interview guide was created, but respondents were encouraged to talk freely about their experiences when deliberating the adoption or non-adoption of SFT. A purposeful sampling method was chosen based on the following criteria: 1) the respondent was a farmer working on-farm with the intention to earn an income or profit, 2) the respondent was a farmer involved in crop production, fruit or vegetable production or livestock rearing, and 3) the respondent was a farmer residing in Europe. These criteria related to the overall scope of the research. A summary of the interviews and how they guided the questionnaire development is available in Appendix A.

4.4.2 Conceptualisation of the Constructs

To test hypotheses, all the variables of interest must be clearly conceptualised and operationalised (Babbie, 2014). Conceptualisation relates to the meaning of the construct while operationalisation is the process of specifying how the variable or construct is measured (ibid). Hair *et al.* (2019b) suggest a five-step construct and scale development process, starting with definition, moving to literature review or interviewing experts, next to face validity, then semantic validation and finally statistical validation. This process was followed in this study and is detailed below. A set of pre-validated measurement items associated with the conceptual model constructs was created, based on the extensive literature review detailed in Chapter 2. Furthermore, interviews with farmers were conducted to help with the development of the measurement items used in the questionnaire, as outlined in Section 4.4.1. Face validity was also conducted with research experts, detailed in Section 4.4.4. Semantic validation was established through the use of a pilot questionnaire, discussed in Section 4.4.6. Statistical validation using Confirmatory Factor Analysis (CFA) and path analysis is explained in Section 4.5. Table 4.2 defines each of the constructs used in the research, based on the extensive literature review conducted.

Table 4.2 Definition of the constructs used in the research

Construct	Conceptual Definition
Section A	**Antecedents to the behavioural intention to adopt SFT**
Personal Innovativeness in the domain of Information Technology (PIIT)	PIIT is defined as the willingness of an individual to try out new information technologies (Agarwal and Prasad, 1998, p. 206) and is based on original work conducted by Midgley and Dowling (1978) and Flynn and Goldsmith (1993). It is deemed a stable personality trait which is not influenced by environmental variables (Rosen, 2004). It was originally developed in the context of the world-wide web but has been used in studies examining both innovative hardware and software (Alkawsi *et al.*, 2021; Ciftci *et al.*, 2021; Fagan *et al.*, 2012). The items used to measure PIIT relate to typical behaviours in the IT domain (Agarwal and Prasad, 1998).
Social Influence (SI)	Interactions with others in the farmer's network affects the diffusion and adoption of innovation in agriculture (Giua *et al.*, 2022). Social influence is described as the degree to which an individual perceives that important others believe that he or she should use the new system (Venkatesh *et al.*, 2003). People who influence the participant's behaviour and people important to them are measured separately in the construct.
Perceived Ease of Use (PEOU)	Perceived Ease of Use is defined as the degree to which an individual believes that using a particular system would be free of physical and mental effort (Davis, 1986, p. 26). It is a behavioural construct and a determinant of behaviour (Davis, 1989).
Perceived Usefulness (PU)	Perceived Usefulness describes the degree to which an individual believes that using a particular system would enhance his or her job performance (Davis, 1986). This is also a behavioural construct and relates to job effectiveness, productivity, and time savings (Davis, 1989).
Trust	Trust is defined as a cognitive process where there is a willingness of a party (i.e., the farmer) to be vulnerable to the actions of another party (i.e., the SFT vendor). This is based on the expectations that the other party will perform a particular action important to the trustor, irrespective of the ability to monitor or control (Mayer *et al.*, 1995). Trust is a set of a specific beliefs from the trustor relating to the integrity, benevolence, and competency of the trustee. Consequently, trust is a second-order factor in this research.
Attitude (ATT)	Attitude is described as an individual's degree of evaluation toward a target behaviour (Ajzen and Fishbein, 1980). In this research, attitude relates to the farmer's evaluation towards using SFT. Attitudes can be

	favourable or unfavourable and are formed using attribute dimensions related to the behaviour (Ajzen, 2001).
Section B	**Multiple dimensions of Trust**
Integrity	Integrity is a dimension of trust and relates to the trustor's (i.e., the farmer's) perception of the honesty, character, and motives of the trustee (i.e., the SFT vendor) (Connelly *et al.*, 2015).
Competency	Competency is also a dimension of trust and relates to the trustor's (i.e., the farmer's) perception of the knowledge, ability, and reliability of the trustee (i.e., the SFT vendor) to fulfil their promises and obligations (Mayer *et al.*, 1995; Saleh *et al.*, 2013).
Benevolence	Benevolence as a dimension of trust refers to the trustor's (i.e., the farmer's) perception of the trustee (i.e., the SFT vendor) as caring about the organisation or an individual's needs beyond making a profit (Mayer *et al.*, 1995; Svare *et al.*, 2019).
Section C	**Dependent Variable**
Behavioural Intention (BI)	Behavioural Intention is the probability that an individual will perform a specific behaviour (Fishbein and Ajzen, 1975). In the context of this study, it is the probability that a farmer will adopt SFT. There is a strong correlation between the intention to adopt technology and actual usage (Venkatesh *et al.*, 2003).
Section D	**Moderating Variables**
Age	Age is a demographic variable indicating the time frame in years since the birth of the farmer. In this study, it is treated as a moderator on the relationship between perceived usefulness and behavioural intention, and attitude and behavioural intention.
Gender	Gender is a demographic variable which is defined as the individual's biological sex as opposed to gender as a social construct which incorporates behavioural, social, and psychological characteristics (Venkatesh and Morris, 2000). Gender is treated as a moderating variable on the relationship between perceived usefulness and behavioural intention, and attitude and behavioural intention.
Education	Education is also a demographic variable and relates to the highest level of education that the farmer has achieved. Education is also treated as a moderating variable on the relationship between perceived usefulness and behavioural intention, and attitude and behavioural intention.
Farm Size	Farm size relates to the sum of land in hectares that is cultivated by the farmer for either vegetation or animal rearing or breeding (Noack and Larsen, 2019). Farm size is also treated as a moderator on the relationship between perceived usefulness and behavioural intention, and attitude and behavioural intention.
	Control Variable
SFT experience	SFT experience outlines the respondent's perception of whether they have previous experience of using Smart Farming Technology.

Furthermore, the categories of SFT examined in this research are based on the definitions used by Kernecker *et al.* (2021) and Balafoutis *et al.* (2020) classifying the technologies into three categories: 1) farm management information systems (FMIS) that manage data to support farm operations, 2) precision agriculture (PA) systems and GNSS (global navigation satellite systems) and, 3) automated systems such as robotics and artificial intelligence.

4.4.3 Operationalisation of the Constructs

Developing scales and measurement items based on previously determined theoretical considerations is critical in research (Rossiter, 2002). A deductive approach was used for scale development, consistent with the researcher's positivistic and objective views on epistemology and ontology. Hair *et al.* (2019b) explains that multiple items are needed to measure a latent construct or variable. These measures are either reflective or formative, depending on the relationship between the items and the construct (Hanafiah, 2020). Coltman *et al.* (2008) outlines that three theoretical considerations must be considered in deciding if the associated measurement model is reflective or formative. These include 1) the type of construct, 2) the direction of causality between the variable and its indicators and, 3) the characteristics of the items used in the measurement of the latent construct. Reflective measures signify indicators or consequences of the variable and represent causality from the construct to the measurement items (Hanafiah, 2020; Howell *et al.*, 2007). Diamantopoulos and Siguaw (2006) describe this scenario as the construct giving rise to the items or indicators. Reflective models are typically used in classical theory (Jarvis *et al.*, 2003). For example, measures of attitude and personality are typically reflective (Coltman *et al.*, 2008). With a reflective model, high and positive correlations between the measurement items exist (Christophersen and Konradt, 2012). Therefore, tests to measure factor loadings such as Cronbach's Alpha, average variance extracted, and internal consistency are important to determine the reliability of the reflective measures (Hair *et al.*, 2021a; Jarvis *et al.*, 2003). Coltman *et al.* (2008) and Diamantopoulos and Siguaw (2006) stipulate that most scholarly research in the marketing and organisational behaviour domains assume that the relationship between items and the construct is reflective. Indeed, Howell *et al.* (2007) and Bagozzi (2007b) recommend using reflective measures. Alternatively, with formative measures, the construct is defined by the indicators or items. Diamantopoulos and Siguaw (2006) describes this as the indicators defining the construct. A strong correlation between measurement items is not theoretically essential (Fornell and Bookstein, 1982). Howell *et al.* (2007) argues that formative measurements do not claim that the construct exists outside the measurement items.

In structural equation modelling (SEM), the principal factor model where covariation between the measures exists, relies on reflective measures while the composite latent variable model uses formative measures (Jarvis *et al.*, 2003; Liu *et al.*, 2012). Thus, Anderson and Gerbing (1988) highlight that it is important for the researcher to clearly explain the type of measure used, as it impacts the specification of the measurement model and the relationships in the structural model. However, the choice of measurement perspective should be driven by theory (Diamantopoulos and Siguaw, 2006). In this study, reflective model measures are used as the indicators are stipulated as being a manifestation of the construct. Furthermore, the indicators share a common theme and are expected to have a strong correlation with each other. Therefore, all first order factors in this research model are reflective measures using indicators from the extant literature. Trust, which is a second-order factor, also uses reflective measures of integrity, competency and benevolence, as sourced in the literature. This is consistent with the approach taken by several studies examining trust (Akter *et al.*, 2011; Huang *et al.*, 2022; Kohring and Matthes, 2007; McKnight *et al.*, 2011). Furthermore, Gefen (2004) argues that a reflective-reflective second order model is appropriate for trust. Analysis of the internal consistency and correlation between items in each construct is presented in Section 4.5.4.1.

4.4.3.1 Antecedents to the Behavioural Intention to adopt SFT

The integrated, conceptual model in this research hypothesises the factors which influence the farmer's behavioural intention to adopt SFT. These consist of personal innovativeness, social influence, perceived usefulness, perceived ease of use, trust in the SFT vendor and attitude towards using SFT. The conceptualisation of each construct is subsequently discussed. Multi-item measurement scales were used for all constructs to ensure reliability and validity.

Personal Innovativeness in the IT domain: This construct was developed by Agarwal and Prasad (1998) derived from the original work of Midgley and Dowling (1978) and Flynn and Goldsmith (1993). Agarwal and Prasad (1998) specified the concept more clearly by adding the specific domain of IT. As outlined in Section 2.8.5.2, the construct is important in identifying individuals who are likely to adopt technology earlier than their counterparts and consequently play an important role in the diffusion of innovations. The four items used by Agarwal and Prasad (1998) in their original study were adopted in this study. Table 4.3 outlines the operationalisation of all constructs, the reliability measures specified in the literature and the final items used in the questionnaire.

Social Influence: Social influence is conceptualised in this study as a cognitive process. The measures are adopted from the scale used in the Unified Theory of Acceptance and Use of Technology Behaviour (UTAUT) developed by Venkatesh *et al.* (2003). This scale was based on the subjective norm work from previous researchers, namely Fishbein and Ajzen (1975), Taylor and Todd (1995) and Davis *et al.* (1989). It was developed specifically for the context of technology adoption and is measured by two items associated with identification and compliance. The items were adjusted slightly to relate to the specific behaviour of SFT adoption. Appendix B outlines the original scales and the modifications for this research. Specific measures of social influence related to members of the farmer's network, namely peer farmers, farm family, farm advisor, farming association and farming co-operative were also captured for descriptive purposes.

Perceived Usefulness: Perceived Usefulness is conceptualised as a cognitive response (Davis, 1986). The scale was developed by Davis (1989) for the Technology Acceptance Model. Development and validity testing of the scale was confirmed by Davis (1989) using two separate studies, each testing three distinct technologies. Furthermore, Davis and Venkatesh (1996) indicate strong psychometric properties for the scale. Convergent validity, discriminant, and factorial validity for the scale were supported. Six items are used to measure the construct, related to improved productivity, job performance and effectiveness. Again, each of the items in this study were adjusted slightly, as detailed in Appendix B, to account for the context of SFT adoption. The original scale has been used and adapted for numerous studies in agriculture using TAM (Aubert *et al.*, 2012; Chuang *et al.*, 2020b; Flett *et al.*, 2004; Kelly *et al.*, 2015; McCormack *et al.*, 2021; Mohr and Kühl, 2021; Naspetti *et al.*, 2017; Zheng *et al.*, 2018).

Perceived Ease of Use: Perceived Ease of Use is also conceptualised as a cognitive response (Davis, 1986). The construct was also developed by Davis (1989) in his work on TAM. The scale was used by Venkatesh and Davis (1996) in their work on determining the antecedents to PEOU. It is recognised as having strong psychometric properties (Davis and Venkatesh, 1996). Development and validity of the scale was confirmed in the same research conducted for PU from Davis (1989) using two separate studies. Convergent validity, discriminant, and factorial validity for the scale was supported. PEOU is represented by the individual's perceptions regarding the technology being easy to use, easy to learn, easy for the user to become skillful at and that their interactions with the technology would be clear. Again, each of the items were adapted slightly, as outlined in Appendix B, to account for the context of SFT. The original scale has also been used and adapted for numerous TAM studies in agriculture, taking into account the specific technology, as outlined in the PU section above.

Trust: As outlined in Section 2.8.5.3, trust is a second order factor as recommended by Jarvis *et al.* (2003). It is multidimensional and made up of first order factors namely, integrity, benevolence and competency (Mayer *et al.*, 1995). Multiple scales are available to measure trust, but the scale used in this research was adopted from McKnight *et al.* (2002), based on original work from Mayer *et al.* (1995). McKnight *et al.* (2002) empirically validated their measures for the trust construct with discriminant validity and both internal and external nomological validity confirmed. Integrity is measured by three items measuring honesty, reliability and sincerity. Competency is measured by three items related to ability and capability and benevolence is measured by three items regarding goodwill and altruism. Appendix B details the original scale and the modifications for this research. Trusting propensity was also captured for descriptive purposes. This was measured using the scale from Mayer and Davis (1999, p. 136) which uses statements related to the propensity to trust in action, such as “Most experts tell the truth about the limits of their knowledge”.

Other trust scales were examined. For example, Gefen (2004) developed a scale to measure trust in enterprise resource planning implementation using scales from similar research examining trust in buyer-seller scenarios, trust in specialised consultants and trust in business agents. This scale used two items for integrity, two items for competency and one for benevolence, incorporated into one single scale. Gefen (2004) debates that the three beliefs overlap and therefore a single scale is sufficient. However, it is argued that trust as a second-order construct is more appropriate as it offsets multicollinearity concerns. Furthermore, capturing the three trust components in a single latent variable allows for structural analysis, while the individual components are also available in the correlation matrix for interpretation.

Attitude: The attitude towards using SFT construct is adopted and modified from Davis (1986) and Taylor and Todd (1995) which conceptualise attitude as an affective response. Once the individual (i.e., the farmer) develops beliefs about the behaviour (SFT usage), they concurrently develop an attitude. The measure was used in a technology acceptance context for the development of TAM. The work from Davis (1986) is based on the work of Fishbein and Ajzen (1975). Hence, four attitude dimensions which are deemed emotional responses were used in this research, relating to good/bad, wise/foolish, like/dislike and pleasant/unpleasant measures, as recommended by Ajzen (2001).

Behavioural Intention: Behavioural intention is influenced by the individual's beliefs regarding the system or technology under study (Davis, 1986). It is measured using a two-item scale adapted from Davis *et al*. (1989) and Venkatesh (2000). Venkatesh *et al.* (2003) determine that this measure is extensively used in research.

Table 4.3 summarises the measurement items used and also outlines the operationalisation of the moderator variables.

Table 4.3 Operationalisation of the constructs

Factors influencing the farmer's behavioural intention to adopt SFT	
Construct	*Measurement Item*
Personal Innovativeness in the domain of Information Technology taken from Agarwal and Prasad (1998), α=.84.	*The following questions relate to your assessment of yourself:* • If I heard about a new technology, I would look for ways to experiment with it. • Among my peers, I am usually the first to explore new technologies. • In general, I am hesitant to try out new technologies (R). • I like to experiment with new technologies.
Social Influence adopted from Venkatesh *et al.* (2003), α=.88[1].	*The following questions relate to the influence that others may have on your adoption of Smart Farming Technology:* • People who influence my behaviour would think that I should use Smart Farming Technology. • People who are important to me would think that I should use Smart Farming Technology.
Perceived Ease of Use adopted from Davis (1989) α=.94.	*The following questions aim to understand how you feel regarding the ease of use of Smart Farming Technology:* • In general, learning to operate Smart Farming Technology would be easy for me. • In general, I would find it difficult to get Smart Farming Technology to do what I want it to do (R). • In general, my interaction with Smart Farming Technology would be clear and understandable. • In general, I would find Smart Farming Technology to be flexible to interact with. • In general, it would be difficult for me to become skillful at using Smart Farming Technology (R).

[1] Venkatesh et al., 2003 used three target groups for their development of UTAUT. The internal consistency reliability range for Social Influence was .88, .92 and .94 each group.

	• In general, I would find Smart Farming Technology easy to use.
Perceived Usefulness adopted from Davis (1989) α=.98.	*The following questions aim to understand how you feel regarding the usefulness of Smart Farming Technology.* • In general, using Smart Farming Technology would enable me to accomplish tasks more quickly. • In general, using Smart Farming Technology would improve my job performance. • In general, using Smart Farming Technology would increase my productivity. • In general, using Smart Farming Technology would reduce my effectiveness on the job. (R) • In general, using Smart Farming Technology would make it harder to do my job. (R) • In general, I would find Smart Farming Technology useful in my job.
Trust (Integrity) adopted from McKnight *et al.* (2002), α=.88.	*The following questions relate to your opinion of companies that sell Smart Farming Technology, otherwise known as SFT vendors:* • I would be comfortable relying on SFT vendors to meet their obligations. • I would feel fine doing business with SFT vendors since they generally fulfil their agreements. • I would feel confident that I can rely on SFT vendors to do their part when I interact with them.
Trust (Competency) adopted from McKnight *et al.* (2002), α=.92.	*The following questions relate to your opinion of companies that sell Smart Farming Technology, otherwise known as SFT vendors:* • In general, most SFT vendors are competent in their field. • Most SFT vendors do a capable job at meeting farmers' needs. • I feel that most SFT vendors are good at what they do.
Trust (Benevolence) adopted from McKnight *et al.* (2002), α=.96.	*The following questions relate to your opinion of companies that sell Smart Farming Technology, otherwise known as SFT vendors:* • I feel that most SFT vendors would act in a farmer's best interest. • If a farmer required help, most SFT vendors would do their best to help. • Most SFT vendors are interested in farmers' well-being, not just their own well-being.
Propensity to Trust adopted from Mayer and Davis (1999).	*The following questions relate to your general trusting beliefs, they are not related specifically to SFT vendors:* • In general, people really do care about the well-being of others. • The typical person is sincerely concerned about the problems of others. • Most of the time, people care enough to try to be helpful, rather than just looking out for themselves. • In general, most people keep their promises. • I think people generally try to back up their words with their actions.

	• Most people are honest in their dealings with others. • I believe that most professional people do a very good job at their work. • Most professionals are very knowledgeable in their chosen field. • A large majority of professional people are competent in their area of expertise. • I usually trust people until they give me a reason not to trust them. • I generally give people the benefit of the doubt when I first meet them. • My typical approach is to trust new acquaintances until they prove I should not trust them.
Attitude adopted from Davis (1986); Taylor and Todd (1995) and Ajzen (2001).	*The following questions aim to understand your overall attitude to using Smart Farming Technology:* • In general, using Smart Farming Technology would be a good idea. • In general, I like the idea of using Smart Farming Technology. • In general, using Smart Farming Technology would be unpleasant (R) • In general, using Smart Farming Technology would be wise.
Behavioural Intention adopted from Venkatesh *et al.* (2003), α=.90[2])	*The following questions aim to understand your intention to adopt any Smart Farming Technology in the future:* • I intend to use Smart Farming Technology in the future. • Assuming I had access to Smart Farming Technology, I predict that I would use it.

(R): Item was negatively worded and subsequently reverse-coded in the analysis.

4.4.3.2 Descriptive Data

A series of questions related to farming; alongside demographic information was included in the research. The farming-related questions were associated with farm type, farm size, role on farm, legal status of the farm, farming experience and whether the respondent was a full-time or part-time farmer. Demographic questions related to age, gender, level of education, and country of origin. Furthermore, a question was asked to determine the farmer's level of experience in using SFT. The complete set of demographic and farming-related questions is available in Appendix C.

[2] Venkatesh *et al.*, 2003 used three target groups for their development of UTAUT. The internal consistency reliability for Behavioural Intention ranged from .90 to .92.

4.4.4 Design of the Data Collection Instrument

The use of surveys in research is open to common method variance or bias, therefore careful design of the instrument is critical (Tehseen *et al.*, 2017; Walters, 2021). The online questionnaire used in this research was designed and administered using a paid version of the SurveyMonkey software platform. This was used as the data collection instrument for both the pilot survey and the final survey. As outlined by Reavey *et al.* (2021), such platforms offer faster turnaround times, cost savings and ease of data analysis. Accordingly, a tailored, respondent-friendly design was created, based on the target audience of interest (i.e., farmers), the topics being covered, the resources available and the timeframe for producing results. The full survey is available in Appendix C. Ethical concerns related to lack of informed consent, invasion of privacy and deception were considered in the survey design (Bryman and Bell, 2011). Therefore, a brief introduction to the survey was given, presenting the researcher and explaining the reasons for the research, as suggested by Dillman *et al.* (2014). Respondents were informed that participation was voluntary and assurances regarding confidentiality and protection of data were also outlined. This is recognised as an effective measure to minimise respondent apprehension and increase completion rates (Podsakoff *et al.*, 2003; Walters, 2021). Data protection was maintained during the study with data stored carefully and password protected. Furthermore, contact details of the researcher and supervisors were provided in the introduction, if respondents had any further queries. An incentive of a gift card prize for one respondent was offered to increase participation rates. Dillman (2014) notes that material incentives can increase completion rates.

A funnelling procedure was followed where questions followed a logical order, starting from generic to specific, as recommended by (Krosnick and Presser, 2010; Podsakoff *et al.*, 2003; Stockemer, 2019). Farming related questions were placed at the start which were recognised as easy to answer for respondents. The questionnaire then moved to questions regarding related to SFT usage, including a mixture of Likert scale, rank-order and open-ended questions. Questions regarding the constructs of interests as hypothesised in the model then followed. Podsakoff *et al.* (2003) and MacKenzie and Podsakoff (2012) urge caution with intermixing of different constructs in the survey as this may increase the inter-construct correlations. As some of the survey items were similar, such as Perceived Ease of Use and Perceived Usefulness, intermixing was avoided, and items related to constructs were grouped together. Finally, demographic questions were asked at the end of the survey. This is consistent with Lietz (2010) who recommends placing demographic questions at the end, as the respondent is more likely to feel at ease sharing this information once the survey is complete.

The language used in the questionnaire should be understandable by a diverse range of genders, ages and level of education (Lietz, 2010). Therefore, language was used which was commonplace with farmers, regardless of their demographic information. This was tested both in the pilot survey and in the content analysis. Scale items were clear and concise, avoiding technical jargon and bias and thus limiting item complexity (Krosnick and Presser, 2010; Podsakoff *et al.*, 2003; Stockemer, 2019; Tourangeau *et al.*, 2000). This was assessed during the farmer interviews, pilot testing and expert testing. Fink (2003) and Dillman *et al.* (2014) recommend keeping the length of questions short, in order to keep respondents' attention. Therefore, the expected completion time for the full questionnaire as well as sentence length was considered. Grammatical complexities were kept to a minimum and double-barrelled questions were avoided, as recommended by Fink (2003) and Podsakoff *et al.* (2003). Chyung *et al.* (2018) highlight that mixing negatively and positively worded questions can impact the reliability and validity of the instrument and therefore should be kept to a minimum. To counteract response-set bias, some negatively worded questions were dispersed throughout the survey, but these avoided the use of double negatives and used polar opposites of the concept being measured (e.g., easy to use was replaced by difficult to use), as recommended by Chyung *et al.* (2018). These items were reverse coded in the analysis.

Likert questions with a seven-point scale were used in the survey as they are recognised as being reliable and the inclusion of a middle-option increases both reliability and validity (Lietz, 2010). As this study is concerned with attitudes and perceptions, the use of Likert scale statement questions was deemed appropriate to enable the research question to be answered. The scales were clearly labelled with the anchors 1=strongly disagree, 4=neither disagree nor agree, 7=strongly agree, allowing respondents to quantify the response against a valid statement, as recommended by Krosnick and Presser (2010) and Podsakoff *et al.* (2003). The literature is conflicted regarding the labelling of the scale and whether strongly agree should be on the left- or right-hand side of the scale. Fink (2003) recommends moving from strongly disagree on the left to strongly agree on the right. This procedure was followed but changed for the section on social influence, to further avoid response order bias. Respondents were informed that the scale had changed with 1=strongly agree and 7=strongly disagree. The change in ordering was specifically examined and discussed with respondents and experts following completion of the pilot survey to determine any potential impact.

Demographic information related to the respondents was developed, following the guidelines of Hair *et al.* (2010). Gender, age, level of education, farm size, level of SFT usage as well as other farm-related information was sought. Nominal, ordinal and interval scales were used to capture this information. This data allowed the researcher to put contextual relevance to the respondent's answers, as well as testing the hypotheses related to the influence of moderating variables.

4.4.5 Content Analysis

To determine if indicators accurately represent a construct, it is necessary to assess content validity. Content validity refers to whether the measures of a construct accurately represent all elements of the construct (Hair *et al.*, 2021b) and is important in measurement related to behavioural sciences (Sireci, 1998). Content analysis is particularly important when using reflective measures as Petter *et al.* (2007) and Bollen and Diamantopoulos (2017) determine that such measures should be unidimensional and, thus, individual items can be removed to improve construct validity without impacting the overall content validity. Conversely, judgmental and statistical tests should be conducted to evaluate the content being examined (Sireci, 1998). Judgemental tests are conducted by subject matter experts reviewing the content while statistical tests are carried out through pilot testing (Almanasreh *et al.*, 2019). With judgemental testing, the measures and scales are examined to ensure correct conceptual definition and clear representation and formulation of the items (Wieland *et al.*, 2017). For statistical testing, establishing internal consistency, correlation between items, and convergent and discriminant validity through founded tests is necessary (Rubio *et al.*, 2003).

As outlined in Section 4.4.1, qualitative interviews were conducted with farmers to clarify the constructs related to SFT adoption. This was also used to ensure that the language and terminology used was familiar to farmers. Minor modifications to wording were made, particularly for questions related to farming. Expert academics reviewed the overall questionnaire and each of the scale's items to ensure content validity. Overall, three senior lecturers in South East Technology University (SETU) who hold a PhD examined the content. A senior member of the Irish Farmers' Association (IFA) also reviewed the questionnaire content. Following this review, a pilot study was conducted with a group of final year students from SETU studying Agriculture, as well as recruiting four older farmers (over 40) to complete the survey and give feedback on the content and layout. This is detailed in Section 4.4.6.

4.4.6 Pilot Testing

The questionnaire was pilot-tested prior to full execution to determine reliability and validity and to investigate if any changes were needed, as recommended by Collins (2003). Expert-driven and respondent-driven pretests were completed, consistent with recommendations from Morgado *et al.* (2017). Validity relates to whether the items used to measure a construct accurately represent the construct (Hair *et al.*, 2005b). The data were collected over a period of fourteen days in October 2022. As outlined, the questionnaire was administered to 4th year agricultural students at SETU, as well as four farmers over the age of forty. This was to ensure that the pilot sample accurately represented the sample that would be invited to complete the final questionnaire. Thirty-two respondents fully completed the questionnaire. Feedback from the face validity testing was considered and a number of changes were made. For example, farm size response options were changed based on the advice from one expert, due to the area of a farm being usually treated as a continuous variable. As a result, farm size groups were changed to have common boundaries. Another expert recommended changing SFT experience to a Likert scale item rather than a nominal scale to allow for further investigation. Advice was sought regarding experts' views on changing the order of the Likert scale for one section in the questionnaire. The experts felt it was well explained and would help to limit response bias, while the agricultural students who completed the questionnaire said they were also cognisant of the change. A few students gave feedback that the items in the attitude construct were similar, however as this was consistent with the approach taken by Fishbein and Ajzen (1975), all items remained in the final questionnaire.

Analysis of the pilot survey results demonstrated no issues with reliability. Reliability refers to whether the items used to measure a construct are stable and consistent (Hair *et al.*, 2003; Venkatesh *et al.*, 2003). Internal consistency reliability is commonly used to assess the correlations between different items measuring the same concept (Hair *et al.*, 2005b). The Cronbach Alpha coefficient is generally the most accepted test to ascertain internal consistency or how close items in a scale are related (Field, 2013; Taherdoost, 2016). Normally, values above 0.70 are deemed acceptable (Tavakol and Dennick, 2011).

Results from the pilot showed strong internal consistency with Cronbach's Alpha ranging from 0.759 to 0.899. In some instances, the coefficient could have been slightly improved with the removal of an item from a construct. However, as sample size can affect the Cronbach's Alpha (Bujang *et al.*, 2018) and the sample size was n=32, all items were retained for further statistical analysis in the final questionnaire.

4.4.7 Population and Sampling

Sampling is described as selecting observations to take part in the research, recognising that it is not possible for the entire population of interest to participate (Saunders *et al.*, 2012). Probability sampling infers that the chance of members of a population being selected for study is known (Babbie, 2014; Baker, 2006). Conversely, non-probability sampling which is defined as "*all forms of sampling that are not conducted according to the canons of probability*" (Bryman, 2012, p. 201) was employed for this research. Four types of non-probability sampling exist: reliance on available subjects, purposive, snowball, and quota sampling (Babbie, 2014; Walliman, 2011). Reliance on available subjects or convenience sampling uses participants that are close or convenient to the researcher (Hair *et al.*, 2003). As a result, generalisation and representativeness of the sample can be difficult. Purposive or judgment sampling relies on selecting a sample which the researcher believes will be most useful to the research (Walliman, 2011). With snowball sampling, subjects of the research share or suggest other potential participants, thus relying on individual's social networks (Parker *et al.*, 2019). Quota sampling focuses on representativeness and establishes particular quotas that the researcher needs to fill, often relating to age, gender, ethnicity, or other attributes of interest (Babbie, 2014). All methods of non-probability sampling are open to both conscious and subconscious bias (Baker *et al.*, 2013). Additionally, it is not possible to completely eliminate sampling error with non-probability sampling, but reducing it is possible (Dillman *et al.*, 2014). Following good survey design principles, as discussed in Section 4.4.4 is one method of reducing error.

When using SEM for statistical analysis, having an adequate sample size is important, as smaller sample sizes can deliver unreliable results (Chou and Bentler, 1995; Kline, 2016; Pallant, 2009). Chou and Bentler (1995) recommend n=5–10 per estimated parameter, while Bentler and Dudgeon (1996) determine that a ratio of five respondents per variable is sufficient if the data has a normal distribution and each latent variable has multiple items. Several authors determine that sample sizes generally larger than 200 are necessary for SEM (Byrne, 2010; Dash and Paul, 2021; Hair *et al.*, 2010). However, when determining an adequate sample size, the model complexity, the method used for estimation and type of distribution should be accounted for (Dash and Paul, 2021; Hayes *et al.*, 2017).

This research followed the observations from Chou and Bentler (1995) and Hair *et al.* (2010) of having a minimum of five respondents per variable. Furthermore, as the model was deemed moderately complex with the inclusion of seven latent variables, this stipulation for sampling was deemed suitable. A maximum likelihood estimation method was used, assuming that the variables follow a normal distribution pattern (Beauducel and Herzberg, 2006) as detailed further in Section 4.5. Furthermore, when determining sample size, Malhotra (2010) suggests examining similar studies and the average sample used. Table 2.4 in Section 2.8.6 details other studies using TAM in agriculture and their related sample sizes which vary from 42 respondents to 985, depending on the context, country, and the ability to access state-owned databases related to farmers. For example, Mohr and Kühl (2021) had a sample of 84 farmers in their study on acceptance of artificial intelligence in German agriculture. In their research on the adoption of smartphone apps, Michels *et al.* (2020b) conducted a survey with 207 farmers. They also conducted research on the adoption of drones in agriculture and had a sample of 167 farmers. Chuang *et al.* (2020a) examined IoT use among young farmers involved in field crop production with a sample of 241 respondents, while Naspetti *et al.* (2017) had a total sample of 190 farmers for their research regarding sustainable production strategies among dairy farmers. Flett *et al*. (2004) had a sample size of 985 farmers from New Zealand but had access to a database maintained by an organisation which is part of New Zealand's Ministry of Agriculture and Fisheries.

Additionally, Wolf *et al.* (2013) underlines the importance of achieving sufficient statistical power when determining the appropriate sample size. Power is related to sample size but also equally important is effect size and significance level (typically $\alpha = .05$) (Snijders, 2005). Statistical power is the probability that a statistically significant result will be achieved to reject a null hypothesis (Cohen, 2013). A power analysis was conducted, as detailed in Section 4.5.4.4 and Section 5.5.4 which verified that the model needed at least 200 respondents to detect accurate target effects.

4.4.8 Criteria for Data Selection & Data Collection

The population of interest for this research was farmers involved in livestock rearing, crop cultivation and fruit and vegetable production. Both full-time and part-time farmers were able to complete the survey. Farm owners and farm employees were also eligible, first with the understanding that younger farmers may not yet own a farm but are central to the adoption of new technologies (Holloway *et al.*, 2021). For example, Leonard *et al.* (2017) explains that EU farming is strongly linked to family succession, but the timely transfer of farm ownership is lacking. Conway *et al.* (2022) details that often the senior farming generation are reluctant to change ownership or status quo on their farms. Collective decision-making can therefore emerge in such situations regardless of farm ownership (Maini *et al.*, 2021). Additionally, such family farm employees are seen as influential in providing information to the farmer regarding new technologies (Blasch *et al.*, 2022). Second, Cofre-Bravo *et al.* (2018) note that farm employees' opinions regarding technology adoption can help to shape future innovation decisions. Similarly, Coopmans *et al.* (2021) explain that the future of farming is reliant on farm owners, as well as managers and workers. Thus, understanding the perceptions of farm employees with regard to SFT adoption is important, justifying their inclusion in the survey.

Convenience and snowball non-probability sampling methods were employed for this study. Such methods dominate social science research (Winton and Sabol, 2021). The use of such sampling methods is consistent with other studies examining technology adoption in agriculture. For example, Caffaro and Cavallo (2019) used convenience sampling for their study on SFT adoption by recruiting respondents at an agricultural fair. Mohr and Kühl (2021) recruited respondents from an agricultural university, as well as farmers involved in a project with the university and a water supplier. Negi and Nasreen (2021) used convenience sampling for their survey on farmers' intentions to adopt an electronic trading portal. Naspetti *et al.* (2017) used dairy farm associations, dairy farm events and industry bodies to recruit their sample.

The Horizon 2020 DEMETER project network was leveraged to provide access to farmers participating in the project across Europe but also to farmers who are part of a farmer's organisation involved in the project, such as the Irish Farmers' Association and Teagasc. The survey was also shared online, across various social media platforms. Links to the survey were provided in both print and online publications and the link was also shared by several Teagasc advisors and farmers in farming discussion groups using WhatsApp.

The questionnaire was shared and posted online from 24th November 2022 to 15th March 2023. This was slightly longer than anticipated but necessary in order to fulfil the required sample size and to overcome potential non-response bias. As changes were made to the questionnaire following the pilot testing, it was deemed that these responses could not be included in the final collected sample. Figure 4.1 presents a visual representation of the primary data administration process.

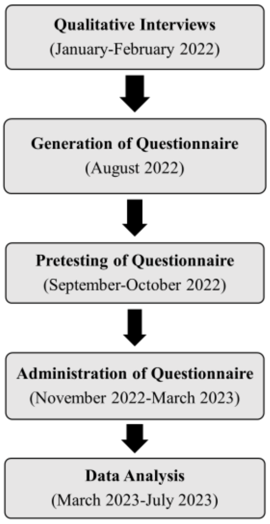

Figure 4.1 Visual representation of the data administration & analysis process

4.5 Data Analysis Plan

A data analysis plan reviews the research questions being examined and the statistical tests needed to assess the various hypotheses (Simpson, 2015). Multivariate analysis is used in this study to analyse and understand the relationships between the variables outlined in Chapter 2. Hair *et al.* (1998) recommend a six-step approach to multivariate analysis, starting with defining the research problem, the research objectives and the multivariate technique to be used. The next stage is developing the analysis plan, followed by evaluating the assumptions underlying the multivariate technique. The fourth stage is estimating the multivariate model and assessing the overall model fit. Stage five relates to interpreting the variate and the final stage is validating the multivariate model. Each of these stages are now discussed in more detail.

4.5.1 Defining the research problem, research objective and multivariate technique

The research problem and objective were detailed in Chapter 2 and 3, with a series of detailed hypotheses and a model specification presented. The overarching objective of the research is to identify the factors which influence farmers' behavioural intention to adopt SFT and to understand the relationships between these factors. A model was subsequently specified which outlined the hypothesised relationships between variables, based on theoretical and substantive justifications, as recommended by Boomsma (2000). This hypothesised model is therefore based on a comprehensive review of the extant literature using the Technology Acceptance Model as the underlying theory, and integrating previously examined constructs such as Social Influence, Personal Innovativeness and Trust. Structural equation modelling (SEM) is selected as an appropriate multivariate technique. SEM is widely used in many social science disciplines (Bagozzi, 1980; Bollen and Long, 1993) and tests hypotheses and relationships among observed and latent variables to build a model (Hoyle, 1995). Hair *et al.* (1998, p.583) define SEM as a "*combining aspects of multiple regression and factor analysis to estimate a series of intercorrelated dependent relationships simultaneously*". It is therefore recognised as being a beneficial tool to model multivariate relationships (Bagozzi, 1980) and is an important instrument for testing theories that use either experimental or non-experimental data (Bentler and Dudgeon, 1996). SEM is defined by two characteristics; 1) the ability to estimate multiple and interrelated relationships between constructs, as discussed, and 2) the capability to represent unobserved concepts in the relationships and their related measurement error (Hair *et al.*, 2019a). As such, SEM is different to other modelling approaches in that it tests both direct and indirect effects of causal relationships (Fan *et al.*, 2016). Nunkoo and Ramkissoon (2012) also highlight that one of the major benefits of SEM over traditional statistics is that all variables are analysed and compared to each other simultaneously, delivering a more comprehensive overview of the model. Regular statistical models typically compare a smaller set of variables and thus may not always present a full depiction of the overall scenario. Classic regression analysis is therefore inadequate for this study as there are several latent variables included in the conceptual model. Thus, SEM is used for the data analysis in this research to examine the cause-and-effect relationships between independent and dependent variables.

SEM is composed of the measurement model which details the factors or the constructs in the model and their corresponding indicators, while the structural model outlines the hypothesised relationships between the constructs (Jarvis *et al.*, 2003; Ullman, 2006). Examining both the measurement and the structural model enables a comprehensive estimation of construct validity (Anderson and Gerbing, 1988). SEM combines two statistical approaches namely factor analysis and structural path analysis, allowing the assessment of both the measurement and structural model in SEM (Fan *et al.*, 2016; Lee *et al.*, 2011). Confirmatory Factor Analysis (CFA) is used to assess the measurement model, determining the model identification and assessing the model fit (Dash and Paul, 2021). Path analysis then examines the relationships among observed variables, accounting for unexplained variance (Mitchell, 1992). This is detailed in Section 4.5.4.

Two SEM approaches exist: covariance-based SEM (CB-SEM) (Jöreskog, 1978) and variance-based partial least squares (PLS-SEM) (Lohmöller, 1989). The two approaches are fundamentally based on different measurement philosophies (Rigdon *et al.*, 2017). CB-SEM is primarily used when there is pre-existing theory to be confirmed, modified, or explained (Hair *et al.*, 2017b; Richter *et al.*, 2016). Furthermore, it allows for the assessment of theoretical models containing second order constructs (Hair *et al.,* 2014a) and error terms in one model (Gefen *et al.*, 2011). The objective of the CB-SEM approach is to estimate the model parameters that minimise the differences between the observed sample covariance matrix estimated (Hair *et al.*, 2012). PLS-SEM is mainly used in exploratory research with the main objective statistically being to maximise the explained variance in the dependent variable(s) or endogenous construct(s) (Hair *et al.*, 2012). Furthermore, a major difference between CB-SEM and PLS-SEM is that the former is based on the common factor model while the latter focuses on the composite model (Hair *et al.,* 2014b). Using composites can result in overestimated loadings and underestimated path coefficients (Goodhue *et al.*, 2012). Both methods have distinct advantages and disadvantages. CB-SEM sum scores are seen as more accurate than PLS-SEM or other regression methods (Goodhue *et al.*, 2012; Hwang *et al.*, 2010) but are based on the assumption of normality (Ong and Puteh, 2017). On the other hand, PLS-SEM is more effective for sample sizes less than 100 and also shows less bias when assessing data from a composite model population (Hair *et al.*, 2017b; Sarstedt *et al.*, 2016). As this research takes a confirmatory approach and intends to modify existing theory, a CB-SEM approach is deemed most suitable. Richter *et al.* (2016) determines that CB-SEM is more appropriate where there is a strong theoretical foundation. As discussed, the constructs used were adapted from previously developed scales from the Technology Acceptance Model. In addition, trust in the SFT vendor is a second-order factor which CB-SEM can assess as part of the theoretical model.

CB-SEM approaches can use multiple software programs such as LISREL, AMOS, EQS and MPlus (Hwang *et al.,* 2010). Each have their own advantages and offer similar functionality, thus no one package is favoured over another (Hair *et al.,* 2014a). IBM SPSS AMOS (Analysis of Moment Structures) is based on covariance using the maximum likelihood (ML) estimation technique and therefore can help confirming theory (Dash and Paul, 2021). ML is discussed in further detail in Section 4.5.2. As a result, AMOS version 28.0 was used for the statistical CB-SEM analysis.

4.5.2 Develop the analysis plan

Hair *et al.* (2010) explain that once the research objectives have been identified and the multivariate technique selected, the next step is clearly developing an analysis plan. This plan includes details related to sample size, the types of variables and the estimation method. Sampling and determination of sample size has been detailed in Section 4.4.7. With the model specification, it is important to identify and reflect on the types of variables and terminology used in the SEM process.

Latent variable: A latent variable in the statistical model is defined as a variable that is unobservable but not unmeasured (Kline, 2014). Chavance *et al.* (2010) explain that the latent variables represent the measurements of a single concept. At least two items or indicators are needed to represent a latent variable (Fan *et al.*, 2016). Second-order latent variables then combine one or more latent variables (Li *et al.*, 2020a). In this research, trust is a second-order latent variable which is represented by three first order latent variables namely benevolence, integrity, and competency. Confirmatory factor analysis is used in SEM to measure latent variables which have been specified according to pre-determined theories or knowledge (Hoyle, 1995; Kline, 2016). Latent variables can be exogenous or endogenous (Hair *et al.,* 2019c).

Exogenous variable: An exogenous variable is external to the model and its value is independent from other variables (Allison, 2009; Hair *et al.*, 2014c). In this research, the exogenous variables are Social Influence (SI) and Personal Innovativeness in IT (PIIT).

Endogenous variable: An endogenous variable is a variable that depends or is determined by its relationship with other variables in the model. Kaplan (2004) determines that in multiple linear regression, one variable is generally referred to as endogenous or the dependent variable while the other variables are exogenous or independent variables. However, in this study Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust (TRU), Attitude (ATT) and Behavioural Intention (BI) are endogenous variables.

Parameter estimation is concerned with obtaining estimates of the free parameters of the model from the observed data (Hoyle, 1995). Several methods for parameter estimation in SEM are possible, such as the maximum likelihood (ML), generalised least squares (GLS) and the Bayesian approach (Deng *et al.*, 2018). CB-SEM uses a maximum likelihood (ML) estimation procedure for parameters (Hair *et al.*, 2014a). This assumes that the data follows a normal distribution pattern (Maydeu-Olivares, 2017). ML is an iterative process which improves "*parameter estimates to minimize a specified fit"* (Hair *et al.*, 1998, p. 581). It is the most commonly used parameter estimation method in SEM (Cheung, 2013; Deng *et al.*, 2018; Li *et al.*, 2020a; Yuan and Bentler, 2007) and is deemed an intuitive and unbiased method that delivers consistent results (Levy, 2012). Furthermore, Hair *et al.* (1998) determine that the method is suitable for sample sizes between 100-500. Therefore, ML was selected as the parameter estimation method for this research.

4.5.3 Evaluate the assumptions underlying the SEM analysis

Assumptions related to normality, linearity, equality of variance and independence of error terms should be assessed following the development of the analysis plan (Hair *et al.*, 2019a). To avoid statistical problems later in the SEM process, the data was prepared and examined to screen for missing values, to assess the normality and linearity of the data and to check for outliers. The objective was to develop a dataset that would allow for accurate analysis. The following sections detail the process followed to examine and prepare the data.

4.5.3.1 Missing data

Missing or incomplete data can occur in datasets due to the respondent not understanding the question, exiting the survey or simply not wanting to answer the question (Malhotra, 2010). Missing data has an effect on the data analysis, therefore the use of complete cases is recommended to allow statistical analysis (Ullman, 2006). Statistical packages allow for estimation of missing data using techniques such as data imputation or pairwise deletion (Ullman, 2006). Conversely, the use of inappropriate methods to handle missing data can lead to bias in parameter estimates, standard errors and test statistics (Allison, 2003).

With the questionnaire used in this research, all questions were marked as mandatory. Therefore, respondents had to either fully complete the survey or exit. As detailed in Section 5.2.1, 507 respondents began the survey of which a total of 227 responses were usable. The reduction in sample size was due to post-hoc screening and incomplete responses. Rigorous post-hoc screening was conducted to ensure the sample reflected the research context. As respondents exited at different stages of the questionnaire, it was not possible to impute missing values due to the large number of items in the survey and the significant number of inter-relationships between constructs. Therefore, missing data was treated with a listwise deletion method. Listwise deletion is the most popular method to deal with missing data and involves the total removal of cases that are incomplete (Byrne, 2010; Schafer and Graham, 2002). Although, it does reduce the sample size, Allison (2009) determines that listwise deletion is a honest method of dealing with missing data. It is acknowledged, however, that farmers who did not complete the survey may have differed from those who did, potentially affecting the representativeness and generalisability of the results. Efforts were made, however, to mitigate this bias with good survey design and extending the time period the survey was open to encourage completion.

4.5.3.2 Outliers

Outliers are data points that deviate or are considered outside the norm for a population (Hawkins, 1980; Rasmussen, 1988). The presence of such outliers can impact the statistical analyses by increasing error variance, decreasing normality and influencing estimates (Osborne and Overbay, 2004). Univariate and multivariate outliers exist; a univariate outlier has a very high value on one variable while the multivariate outlier has an extreme score on more than one variable (Byrne, 2010; Kline, 2005). However, Stevens (1984) determines that not all outliers are influential, therefore it is important to conduct case analysis to determine data points that are both influential and outliers. At the univariate level, boxplots and Q-Q plots can be used to discover the outliers. The boxplot displays the distribution of the data using the median and quartiles (Ghorbani, 2019) while the Q-Q plot compares the quantiles of two probability distributions.

Furthermore, the Cook's distance is used to determine the influence of a data point (Hair *et al.*, 1998). Values greater than 1.0 indicate an influential data point (ibid). At a multivariate level, a Mahalanobis Distance test was conducted which presents observations that have an unusual pattern on several variables (Finch, 2012). Tabachnick and Fidell (2007) recommend a value threshold of 0.001.

4.5.3.3 Sphericity and Sampling Adequacy

The Kaiser-Meyer-Olkin (KMO) test assesses sampling adequacy and whether the data is suitable for factor analysis. Values range from 0 to 1, with values greater than 0.50 indicating that factor analysis is appropriate (Field, 2018). Furthermore, Hutcheson and Sofroniou (1999) determine that values between 0.5 and 0.7 are mediocre, those between 0.7 and 0.8 are seen as good, while values between 0.8 and 0.9 are great and those above 0.9 are excellent. The Bartlett’s Test of sphericity examines whether the sample correlation matrix is significantly different to the identity matrix (Field, 2018; Knapp and Swoyer, 1967). It is recommended that results should be $p < .05$ (Pallant, 2009). The results for the KMO and the Bartlett’s Test of sphericity were assessed against the thresholds outlined.

4.5.3.4 Communalities

Communalities refers to the total amount of variance that a variable shares with the other variables in the analysis (Hair *et al.*, 2010). Generally, items in a factor model should have communalities equal to or greater than 0.50 (Hair *et al.*, 1998; MacCallum *et al.*, 2001). Therefore, all communalities were checked against this threshold.

4.5.3.5 Total Variance Extracted

Total Variance Extracted quantifies how well a set of factors account for the variance in the observed variables (indicators or items) (Hair *et al.*, 2005b). To determine the number of factors to extract from the data, eigenvalues greater than 1 are considered significant (Kaiser, 1960). Eigenvalues represent the amount of variance for a factor and are presented using a scree plot (Jackson, 1993). The total variance test is subjective and states that values which lie below a change in slope should be discarded (Hooper, 2012). A priori theory can also be used to guide this process (ibid). A total variance extracted test was conducted and assessed using the screen plot.

4.5.3.6 Multicollinearity

Multicollinearity relates to an issue in regression analysis where variables in a model are significantly correlated with each other (Mansfield and Helms, 1982). It is measured by using the Variance Inflation Factor (VIF) and Tolerance Value (Craney and Surles, 2002). The VIF is an indicator which outlines "*how much of the estimated regression coefficient is inflated if the independent variables are correlated*" (Shrestha, 2020, p. 40). Values should not exceed 10.0 and ideally be between >1 and <5 (Hair *et al.*, 1998). The Tolerance is the reciprocal of VIF ($1 - R^2$) and values greater than 0.2 are recommended (Field, 2018; Kim, 2019). These thresholds were retained for analysis.

4.5.3.7 Analysis of Descriptive Statistics

One of the fundamental underlying assumptions in SEM is that of normality, which is characterised as a symmetrical, bell-shaped curve and assumes that measurement values are normally distributed around the mean value (Dasgupta and Wahed, 2014). To assess the normality of data, skewness and kurtosis should be evaluated. Skewness refers to the asymmetry of the distribution of a variable, while kurtosis refers to the height and peakness of the distribution (Pallant, 2009). Skewness values to the right are positively skewed while those to the left are negatively skewed (Joanes and Gill, 1998). Hair *et al.* (2022) and Byrne (2010) outline that skewness values between -2 and +2 are acceptable. With kurtosis, values -/+7 are considered acceptable (Hair *et al.*, 2010). A higher and sharper peak (>3) is indicative of a leptokurtic or positive distribution while a lower and broader peak (<3) demonstrates a platykurtic or negative distribution. A mesokurtic distribution is indicative of values =3 (Wright and Herrington, 2011). Values for skewness and kurtosis are assessed against these thresholds outlined. However, it should be noted that Tabachnick and Fidell (2013) state that where the sample size is greater than 200, deviation from the normal skewness and kurtosis values does not make a significant difference to the analysis. Furthermore, analysis of Quantile-Quantile (Q-Q) plots for each variable can also determine if the distribution of the data matches a theoretical distribution (Marden, 2004). Q-Q plot analyses are a more robust way to determine normality, if the data is plotted along a straight line, it can be assumed that data is normally distributed (Ferré, 2009).

4.5.4 Estimate the model and assess overall fit

With the assumptions satisfied, the next stage is to estimate the model and assess its overall fit (Hair *et al.*, 1998). The first step is model identification which focuses on the correspondence between the known information in the model, which is the observed variances and covariances, and the unknown information which is the model parameters to be estimated (Kenny and Milan, 2014; Kline, 2016). It is essentially a feasibility check of the model to determine if there is at least the same amount of observed information as model parameters (ibid). Consequently, models can be over-identified, just-identified, or under-identified (Fan *et al.*, 2016). To examine the model identification, each of the latent variables must have a scale and the degrees of freedom must be at least zero (dfM $\geq$ 0) (ibid). The degrees of freedom are "*the number of bits of information available to estimate the sampling distribution of the data after all model parameters have been estimated*" (Hair *et al.*, 1998, p. 579). Models that do not achieve dfM $\geq$ 0 are classified as underidentified. The model identification will be established if dfM $\geq$ 0.

Next, model evaluation assesses the model and focuses on the degree of model fit (Chin *et al.*, 2014; Fan *et al.*, 2016). Model fit refers to how well the model explains the data (Kline, 2016). Using CB-SEM, the measurement model should firstly be assessed followed by the structural model (Awang *et al.*, 2015). As outlined in Section 4.5.1, the model is reflective which outlines that the latent construct causes variation in the associated set of measures (Hanafiah, 2020). To assess this reflective measurement model, internal consistency reliability of each construct as well as convergent and discriminant validity should be founded (Hair *et al.*, 2017b). Failing to test the reliability and validity of the research constructs could lead to inaccurate conclusions (Fornell and Larcker, 1981). Each of these elements is discussed below.

4.5.4.1 Reliability and Validity

Construct reliability (CR) assesses the extent to which a variable or set of variables is consistent in measuring what it intends to measure (Straub *et al.*, 2004). Richter *et al.* (2016) recommend that researchers assess both the Cronbach's Alpha and composite reliability measures to determine reliability. Cronbach's Alpha compares the covariance between items in a construct to the overall variance amount (Collins, 2007). A Cronbach's Alpha result of 0.70 or higher is generally offered as acceptable reliability (Hair *et al.*, 2019a; Nunnally and Bernstein, 1994). SPSS version 26.0 was used to measure Cronbach's Alpha and benchmarked against the value of >.70 as outlined. Composite reliability is seen as a more reliable indicator of construct reliability (Fornell and Larcker, 1981). Values equal to or greater than 0.60 are deemed acceptable for reflective models (Bagozzi and Yi, 1988). Again, this threshold was used for the analysis. Nomological validity tests should also be conducted to determine CR. Bagozzi (1981, p. 327) describes nomological validity as "*the degree to which predictions in a formal theoretical network containing a construct of interest are confirmed*". Essentially, it relates to whether the correlations among variables are reflected in theory (Lee, 2019). Hagger *et al.* (2017) explain that nomological validity should be supported through examining the correlations between constructs.

4.5.4.1.1 Convergent and Discriminant Validity

Validity is concerned with assessing whether the research instrument measures the construct it contends to measure (Saunders *et al.*, 2012). To measure validity, two checks are recognised as important to conduct, namely Convergent Validity (CV) and Discriminant Validity (DV) (Bryman and Bell, 2011; Henseler *et al.*, 2009). CV evaluates the degree to which measures of a construct that are theoretically related are actually related (Straub *et al.*, 2004). Items within a factor should be highly correlated or share a high proportion of variance in common (Hair *et al.*, 2019a). Factor loadings should be assessed, with values greater than 0.40 considered acceptable although higher values are preferred (Hair *et al.*, 1998). Furthermore, Fornell and Larcker (1981) suggest using the average variance extracted (AVE) as a criterion for CV. The AVE value indicates how much of the indicator's variance is explained by the latent unobserved variable (Henseler *et al.*, 2009). AVE values greater than 0.50 are deemed acceptable to confirm CV (Bagozzi and Yi, 1988; Fornell and Larcker, 1981; Hair *et al.*, 2019a; Hair *et al.*, 2017b).

Discriminant Validity (DV) assesses the degree to which constructs in SEM are unrelated and distinct (Anderson and Gerbing, 1988; Hair *et al.*, 2014b). The Fornell and Larcker (1981) method of calculating DV expounds that the AVE of each latent variable should be greater than the squared inter-construct correlation (SIC) of other latent variables. Therefore, to test the DV, the AVE should firstly be calculated. This is then followed by calculating the SIC by taking the inter-construct correlations from AMOS and squaring the value. Each AVE value should be compared to the SIC value for the related construct. More recently, Henseler *et al.* (2014) introduced a new method of measuring DV, namely the Heterotrait Monotrait Ratio of Correlations (HTMT). The authors introduced this new method due to issues with the Fornell and Lacker method reliably assessing DV in common research situations. The HTMT test outlines that HTMT ratios close to 1.0 represent DV violations. Henseler *et al.* (2014) therefore determine a cut-off point of 0.85 to determine DV. The HTMT method was originally used for PLS-SEM, but Voorhees *et* *al.* (2015) tested the method for CB-SEM in marketing research. They found that the HTMT method provides a more comprehensive assessment of DV than the Fornell and Lacker method. The authors therefore recommend the HTMT method as more suitable for marketing-based research. DV is determined using both the Fornell and Lacker and HTMT method.

Table 4.4 summarises the threshold levels for validity testing:

Table 4.4 Threshold levels for validity testing

Reliability	Convergent Validity	Discriminant Validity
Cronbach's Alpha > 0.7	CR > (AVE) AVE > 0.50	AVE > SIC HTMT Ratio < 0.85

4.5.4.2 Fit indices

Model fit refers to how the model best represents the data (Hooper *et al.*, 2008). Model fit is assessed using statistical and fit indices (Schermelleh-Engel *et al.*, 2003). Several type of fit indices exist, such as absolute fit indices, relative fit indices, parsimony fit indices and those based on the non-centrality parameter (Tanaka, 1993). Hooper *et al.* (2008) recognise that it is not possible to include all fit indices output in the analysis. Hair *et al.* (2010) recommends evaluating a model using at least one index from each category of indices.

- Absolute fit: RMSEA or GFI
- Incremental Fit: CFI, NFI, IFI or TLI
- Parsimonious Fit: Chi-square (X^2) with its degrees of freedom (Df)
- Goodness of Fit Index: CFI or TLI or GFI

Furthermore, Kline (2016) recommends reporting the X^2 and Df and p value; RMSEA, CFI and SRMR. While Schreiber *et al.* (2010) recommends using TLI, CFI, SRMR, and RMSEA. Furthermore, for alternative models, the AIC (Akaike's information criterion) value is commonly used. Based on these recommendations, the following set of indices were chosen for the research: X^2/df and Df, RMSEA, SRMR, IFI, CLI, TLI PNFI as well as the AIC value for testing alternative models. These indices are explained below.

4.5.4.2.1 Absolute fit indices

With absolute fit indices, the researcher's model is assessed and there is no reliance on alternative models to compare with (Jöreskog and Sörbom, 1993). Included in this category of fit tests are Chi-Square test, RMSEA, GFI, AGFI, the RMR and the SRMR (Hooper *et al.*, 2008). The $\chi 2$ or Chi-square value (CMIN) is the original fit index for structural models. If the Chi-square is not significant, the model is regarded as acceptable (Hoyle, 1995). However the Chi-square value is affected by sample size, model size, distribution of variables and omission of variables, therefore researchers have recognised the limitations of this value (Hu and Bentler, 1995). The Chi-square χ^2 /df is more appropriate and measures the minimum discrepancy per degree of freedom or in other words minimises the impact of sample size on the model (Hooper *et al.*, 2008). Generally, values >1 and <3 are deemed acceptable, although in some instances, values <5 are accepted (Kline, 2016; Marsh and Hocevar, 1985).

Further goodness-of-fit indices which should be assessed are the root mean square residual (RMR), and the standardized root mean square residual (SRMR). The RMR is calculated based on the scales used for items in the questionnaire (i.e. scale of 1-5 or 1-7) and can be difficult to interpret as result (Hooper *et al.*, 2008). The Standardised RMR is therefore more appropriate and represents the standardised average value across all standardised residuals (ibid). Hu and Bentler (1999) determine that values < 0.08 are deemed acceptable.

4.5.4.2.2 Relative fit indices

Relative fit indices compare the fit of the hypothesised model with a baseline model or independence model (Xia and Yang, 2019). The Incremental Index of Fit (IFI) addresses parsimony and takes into account the degrees of freedom (Bollen, 1989a). Values over 0.90 are optimum and generally indicative of a model with good fit, but the index can reach values over 1.00 (Hu and Bentler, 1999). Tucker Lewis Index (TLI) also known as the non-normed fit index measures "*a relative reduction in misfit per degree of freedom*" (Shi *et al.*, 2018, p. 311). Generally, values greater than 0.95 indicate relatively good model–data fit (Hu and Bentler, 1999), although values of >0.90 are accepted (Finch, 2020; Hair *et al.*, 1998). It is also recommended to test the TLI between alternative models to determine the best fit (Hair *et al.*, 2005a).

4.5.4.2.3 Parsimony fit indices

Parsimony fit indices penalise models for complexity, with simpler theoretical processes preferred over more complex versions (Kline, 2016). These indices examine the goodness-of-fit of the model in relation to the number of coefficients that are estimated to achieve this level of fit (Hair *et al.*, 1998). The Parsimony Normed-Fit Index (PNFI) is a modification of the NFI and allows for the number of degrees of freedom used to achieve a level of fit (Hair *et al.*, 2019a). There is no threshold for level of acceptance but as with other parsimony fit indices, comparisons should be made with alternative models. When evaluating models, a PNFI difference ranging between 0.06 to .09 indicate substantial differences in the models (Hair *et al.*, 1998). Hooper *et al.* (2008) recommends also comparing the Akaike's information criterion (AIC) values when comparing non-nested models. AIC evaluates the quality of the statistical model for the data sample used, with values closer to zero indicating a better fit model and greater parsimony (Hair *et al.*, 1998).

4.5.4.2.4 Noncentrality-based indices

Noncentrality-based indices estimate model fit against a continuum of models from the null model to the perfectly saturated model (van Laar and Braeken, 2021). The Comparative Fit Index (CFI) outlines the difference between the hypothesised and independent models' non-central Chi-squares. Values close to 1.00 indicate a good fit (Bollen, 1989b). Root Mean Square Error of Approximation (RMSEA) is a value which rewards models that have a larger degree of freedom (Kline, 2016). It is also known as the 'badness of fit' index and Byrne (2010) outlines that values generally < 0.08 are accepted. RMSEA values which are < .05 indicate a close fit, while values closer < .08 suggests a reasonable model fit (Jöreskog and Sörbom, 1993). PCLOSE represents the closeness of fit and thereby tests that the RMSEA value fits the population (Byrne, 2010). A value less than 0.05 indicates that the model does not fit, therefore values >0.05 are recommended to demonstrate close fit (ibid).

4.5.4.3 Common Method Bias

Common Method Bias (CMB) or Common Method Variance refers to the measurement error which can occur relating to the instrument rather than the constructs under study (Podsakoff *et al.*, 2003). Fiske (1982, p. 82) identifies that CMB relates to "*the content of the items, the response format, the general instructions and other features of the test-task as a whole, the characteristics of the examiner, other features of the total setting,* *and the reason why the subject is taking the test*". Development of the survey item should firstly offset the potential of bias, but several statistical tests are available to determine if CMB is present (Rodríguez-Ardura and Meseguer-Artola, 2020). Harman's Single Factor test (Harman, 1967) uses an exploratory factor analysis approach of the indicators in the model to determine if one factor emerges. If the total variance extracted by one factor exceeds 50%, common method bias is present (ibid). However, this method is criticised by several authors for being insensitive and conceptually flawed (Chang *et al.*, 2010; MacKenzie and Podsakoff, 2012; Podsakoff *et al.*, 2003). Bagozzi *et al.* (1991) suggests examining whether the correlations between factors are below <0.90 which illustrates that CMB does not impact the internal consistency of the factors. CMB is assessed against the recommendations of Harman (1967) and Bagozzi *et al*. (1991).

4.5.4.4 Statistical power

As detailed in Section 4.4.7, it is considered good practice to determine the power of the study as part of the analysis (Schumacker and Lomax, 2015). Power of a statistical test determines how likely the study is to detect an actual or true effect (ibid). As such, sample size is an important determinant of statistical power. Power size of >.80 is recommended (Cohen, 1988). The power can be calculated using Preacher and Coffman's RMSEA based technique (Preacher and Coffman, 2006).

4.5.5 Interpret the Variate

Interpreting the variate is also known as model modification which is concerned with the possibility of making changes to achieve a better model (Bollen and Long, 1993; Chin *et al.*, 2014; Hoyle, 1995; Kline, 2005). Alongside a confirmatory modelling strategy, assessing any possible model specifications as well as competing models is necessary (Hair *et al.*, 1998). Consequently, model comparisons are an important stage in the structural model analysis (Rigdon *et al.*, 2017). A number of techniques were used such as nested model testing approach, mediation analysis, testing alternative theories and moderation analysis as outlined below.

4.5.5.1 Initial Structural Model and Nested Models

It is advised that the fit of the hypothesised model and control variables is compared to the fit of alternative and nested models (Hoyle, 1995). Nested models are categorised as being subsets of the original model (Ullman, 2006). This nested model testing can be done by changing the direction of one or more of the paths in the original model or fixing one or more of the free parameters (Bentler and Satorra, 2010). The parameters used to test nested models include a Chi-square difference test, also known as a likelihood ratio test, using the Chi-square values and degrees of freedom (Melas *et al.*, 2011). The likelihood ratio test is the difference between the $\chi 2$ values of the full and reduced models, as well as the difference of the degrees of freedom (Vuong, 1989). Values are compared against a Chi-squared table. If the p-value is <0.05, constrained or nested model represents a significantly worse fit to the data than the unconstrained model. However, other fit indices, as previously outlined, should also be compared for parsimony, as should the substantive theory already examined (Bentler and Satorra, 2010). Comparing nested models can result in a model with better fit or a more parsimonious model.

4.5.5.2 Mediation Analysis

Following the structural model and nested model analysis, mediation tests are necessary to conduct, as the proposed conceptual model presents multiple potential mediation paths. Mediation in research involves including an additional variable between X and Y variables and is an important concept in social sciences (MacKinnon, 2008). Multiple regression tests using a bootstrapping approach to assess the significance of the indirect effects is recommended (Hair *et al.*, 2010). Bootstrapping is a form of resampling taking the original data and repeatedly creating new samples for model estimation (Hair *et al.*, 1998; Mooney and Duval, 1993). The process enables the handling of multivariate nonnormal data and allows for assessment of the stability of parameter estimates (Byrne, 2010). The process is conducted in four steps. First, use the original sample as the population. Next, resample the original sample a specified number of times; at least 5,000 times is recommended. Third, estimate the model for each sample and save the estimated parameters, resulting in an empirical sampling distribution. Finally, calculate the parameter estimates as the average of the parameters estimates across all the samples (Hoyle, 1995).

Several mediation testing methods are possible such as path analysis, bootstrapping and the Sobel test (Fairchild and MacKinnon, 2009). Multiple regression analysis with bootstrapping was selected, as one of the major limitations of the Sobel test is its unrealistic assumptions regarding the shape of the sampling distribution (Preacher and Hayes, 2004). The “PROCESS" macro, model 4, v4.2 (Hayes, 2022) in SPSS version 26 with bias-corrected 95% confidence intervals (n = 5000) was used to test the significance of multiple indirect effects (i.e., mediated). Significant effects are supported by the absence of zero within the confidence intervals (Preacher and Hayes, 2004). Each path in the proposed mediation was firstly tested for significance. If both the a-path (from the independent variable to the mediator(s)) and the b-path (the direct effect of the mediator(s) on the dependent variable) were significant, the mediation analysis was conducted using the PROCESS macro bootstrapping method, outlined above. As part of this test, full or partial mediation was assessed through examination of the independent variable on the dependent variable, controlling for the mediator(s).

4.5.5.3 Alternative Models

Morgan and Hunt (1994) recommend comparing the initial model to alternatives based on the following terms: 1) overall fit of the model, using the CFI indicator, 2) parsimony, using the PNFI value, 3) percentage of the model paths that are statistically significant; and 4) the ability to explain the variance in the outcomes of interest using the squared multiple correlations of outcome variables. Squared multiple correlations determine how much of the variation in a dependent variable is accounted for by the independent variables associated with it in the model (Kwan and Chan, 2014). Values closer to 1 indicate a larger proportion of the variance in the endogenous variable is accounted for by the predictors (Hoyle, 1995). Tests were therefore conducted with alternative models, based on theory, to determine if alternative paths were necessary.

4.5.5.4 Moderation Testing

As the conceptual model contains several moderation paths, hierarchical moderation linear regression tests were conducted. The “PROCESS" macro, model 1, v4.2 (Hayes, 2022) in SPSS version 26 with bias-corrected 95% confidence intervals (n = 5000) was used to test interactions at various levels of the moderator. To establish if the moderator effect is significant, the original relationship should first be determined (Hair *et al.*, 2010). The moderated relationship should then be assessed and if the change in R^2 is significant, then it can be determined that a moderator effect is present. Tests were conducted across each of the moderators (age, gender, education and farm size) to determine their effect on the relationships between perceived usefulness and behavioural intention, and attitude and behavioural intention.

4.5.6 Validate the Multivariate Model

Following these diagnostic measures, the researcher must determine if the data is generalisable and not just applicable to the sample under observation (Hair *et al.*, 2019a). Cross validation is one method to assess generalisability between models which are theoretically plausible (Cho *et al.*, 2019). The Expected Cross Validation Index (ECVI) from Browne and Cudeck (1993) evaluates how well the specified model would fit with another sample of similar size (Kaplan, 2004). Schermelleh-Engel *et al.* (2003) indicates that a smaller ECVI estimate indicates the model which has the best fit. The ECVI value of models was thus assessed.

4.6 Conclusion

In this chapter the various research philosophies and their views on ontology and epistemology were outlined. The researcher's chosen philosophical approach of objectivism and positivism were presented and thus a deductive approach was followed. Several research methodologies were discussed, with the researcher selecting a quantitative approach using an online, structured questionnaire as the chosen data collection method. A causal, non-experimental research design was followed with the objective of determining cause and effect relationships between the variables in the conceptual model. The questionnaire development process was summarised which detailed the conceptualisation and operationalisation of the constructs in the conceptual model, the pilot testing procedure and the non-probability sampling approach adopted. Finally, the data analysis plan was presented with co-variance-based SEM selected as the multivariate technique. An explanation of the statistical test thresholds against which the conceptual model can be tested were also explained. The next chapter presents the results of the statistical tests conducted and the hypotheses testing.

Chapter 5: Analysis

5.1 Introduction

In this chapter, the results of the analysis and hypothesis testing are discussed. The first section, 5.2, examines the statistical data, giving an overview of the survey response rate, the pre-structural equation modelling (SEM) analysis conducted and a descriptive overview of the survey respondents. The next section, 5.3, details the reliability and validity tests completed as part of the preliminary data analysis, while Section 5.4 examines the model constructs. Section 5.5 details the analysis of the measurement model, while Section 5.6 explains the SEM process undertaken. IBM SPSS Amos 28.0.0 was utilised for this analysis. Following this, Section 5.7 specifies generalisation and Section 5.8 presents the hypotheses test results. A brief conclusion is presented in Section 5.9.

5.2 Examination of Statistical Data

5.2.1 Response Rate

The online questionnaire was shared using several social media channels and email. Several agri-publications (online and print) shared an overview of the questionnaire and a link to where it could be found online. Samples from these publications are shared in Appendix D. The questionnaire was also shared with several agri-associations, both members and non-members of the DEMETER consortium, such as the World Farmers' Organisation (WFO), Irish Farmers' Association (IFA), Romanian Maize Growers' Association (APPR) and Macra na Feirme, who promoted it among their memberships. In total, 631 respondents opened the questionnaire with 29% choosing to read the detailed background to the research, and the remaining 71% proceeding directly to complete the survey. 507 respondents started the questionnaire, of which a total of 227 responses were usable. As discussed in Section 4.4.7, post-hoc screening was conducted to ensure the sample matched the research context. Respondents exited at different stages of the questionnaire, initially following questions related to farming and then a large majority exited before adding their demographic information. Non-response bias could be evident, although pilot testing was conducted to ensure optimal survey design and the survey was open for approximately three months to allow completion. Missing data was treated with a listwise deletion method, as referred to in Section 4.5.3. This was necessary due to the nature of the model, the interrelationships, and the need for demographic data to test the moderation hypotheses. Influential outliers were also removed, as discussed in Section 5.2.2.4.

5.2.2 Pre-SEM analysis

5.2.2.1 KMO and Bartlett's Test

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy shows a value of 0.885, which is above the recommended cut off of 0.800 and indicates the appropriateness of the data for factor analysis. The significance value of the Bartlett's test of sphericity is $p < 0.05$, at 0.000, as outlined in Table 5.1. This demonstrates that there is correlation amongst variables in the model and factor analysis is suitable for the sample collected.

Table 5.1 KMO and Bartlett's Test

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.885
Bartlett's Test of Sphericity	Approx. Chi-Square	4329.685
	df	528
	Sig.	.000

5.2.2.2 Communalities

As outlined in Table 5.2, communalities ranged from .519 to .855, indicating there are no communality issues between the measured items.

Table 5.2 Communalities

Communalities

	Initial	Extraction
INTENT 1	1.000	.528
INTENT 2	1.000	.631
PU1	1.000	.531
PU2	1.000	.682
PU3	1.000	.703
PU4	1.000	.526
PU5	1.000	.683
PU6	1.000	.519
PEOU1	1.000	.706
PEOU2	1.000	.598
PEOU3	1.000	.763
PEOU4	1.000	.703
PEOU5	1.000	.709
PEOU6	1.000	.741
ATT1	1.000	.679
ATT2	1.000	.757
ATT3	1.000	.711
ATT4	1.000	.618
SINF1	1.000	.855
SINF2	1.000	.839
TRU_BEN1	1.000	.550
TRU_BEN2	1.000	.642
TRU_BEN3	1.000	.735
TRU_INT1	1.000	.756
TRU_INT2	1.000	.686
TRU_INT3	1.000	.707
TRU_COMP1	1.000	.801
TRU_COMP2	1.000	.778
TRU_CCOMP3	1.000	.750
PIIT1	1.000	.636
PIIT2	1.000	.726
PIIT3	1.000	.696
PIIT4	1.000	.723

5.2.2.3 *Total Variance Extracted*

Exploratory Factor Analysis was conducted to determine the factors which account for the variance in the observed variables. A total of seven factors were extracted (i.e., components with eigenvalues greater than 1.0), as outlined in Table 5.3, accounting for 69% of the cumulative variance.

Table 5.3 Total Variance Explained, extracted factors

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.126	30.686	30.686	10.126	30.686	30.686
2	4.178	12.659	43.345	4.178	12.659	43.345
3	2.294	6.951	50.296	2.294	6.951	50.296
4	1.995	6.046	56.342	1.995	6.046	56.342
5	1.546	4.685	61.027	1.546	4.685	61.027
6	1.400	4.241	65.268	1.400	4.241	65.268
7	1.131	3.426	68.694	1.131	3.426	68.694
8	.846	2.563	71.257			
9	.762	2.309	73.566			
10	.755	2.288	75.854			
11	.657	1.990	77.844			
12	.599	1.816	79.660			
13	.564	1.708	81.368			
14	.526	1.594	82.963			
15	.506	1.533	84.496			

The scree plot, as presented in Figure 5.1 demonstrates that there are points of inflexion at Factor 3 – 8, demonstrating that the seven-factor solution is appropriate. This is consistent with the conceptual model presented in Chapter 3.

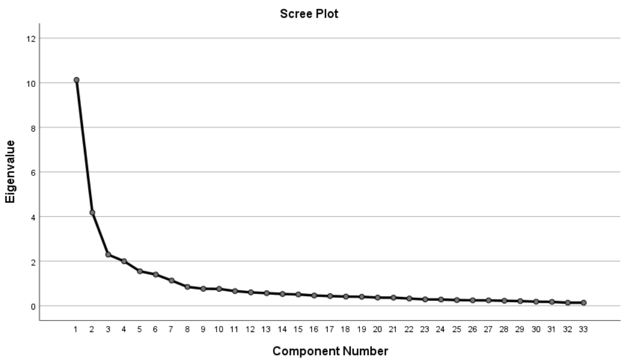

Figure 5.1 Scree plot generated using SPSS 26

5.2.2.4 *Outliers*

Box plots were run, as outlined in Appendix E, to determine if any outliers were present. They suggested that outliers were present for some of the items in PIIT, PU, Trust, ATT and BI. Further analysis was conducted on each of the outliers using univariate and multivariate testing. Casewise Diagnostics using the Cook's Distance test in SPSS illustrated six case numbers which were particularly problematic, as illustrated in Table 5.4. The cases outlined had a residual size which was close to or exceeded 3 and were therefore subsequently removed.

Table 5.4 Casewise Diagnostics Univariate Testing

Casewise Diagnostics[a]

Case Number	Std. Residual	Int_c	Predicted Value	Residual
12	-4.874	1.00	5.2003	-4.20033
21	-3.153	2.00	4.7171	-2.71707
27	-4.017	1.00	4.4617	-3.46166
88	-5.606	1.00	5.8317	-4.83173
89	-3.323	4.00	6.8636	-2.86357
198	-3.112	4.00	6.6823	-2.68233

Multivariate testing was then conducted using the Mahalanobis Distance test to determine multivariate outliers. This revealed a further four cases with issues, as illustrated in Table 5.5.

Table 5.5 Casewise Diagnostics Multivariate Testing

Casewise Diagnostics[a]

Case Number	Std. Residual	All_int	Predicted Value	Residual
170	-5.511	1.00	5.8666	-4.86657
171	-4.769	1.00	5.2117	-4.21169
200	-3.239	2.00	4.8604	-2.86036
211	-4.009	1.00	4.5399	-3.53991

Each of these associated cases and those highlighted in the boxplots were assessed further to determine if they should be deleted. On evaluation of the open-ended questions and the association between different responses, the ten cases identified in the Cook's Distance and Mahalanobis Distance test were deleted, leaving a total valid sample of 217 for analysis.

5.2.2.5 Normality of data

To assess the normality of the data, normal Q-Q plots were created in SPSS. Data normality assumptions were met, as there were no deviations from the patterns observed in the Q-Q plots. A full overview of the normality tests is available in Appendix F. All values for skewness were in the acceptable range of +2/-2, as recommended by Hair *et al.* (1998). Kurtosis values were all within the threshold of +/- 7 indicated by Hair *et al.*

(1998). It is noted that BI displayed a kurtosis of >3 indicating a leptokurtic distribution, containing more extreme values. However, the values are still within the recommended threshold. Skewness and kurtosis for the first order factors in Trust were also within the acceptable thresholds, as outlined in Appendix F.

5.2.2.6 Multicollinearity

Furthermore, collinearity statistics, as outlined in Table 5.6, determine that multicollinearity is not a concern as the Tolerance value is >.10 and VIF value is <10.0, in-line with the recommendation by Field (2018).

Table 5.6 Collinearity Diagnostics

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	1.802	.406		4.436	.000		
	All_PU	.325	.098	.286	3.325	.001	.373	2.678
	All_PEOU	-.014	.065	-.015	-.213	.831	.575	1.739
	All_ATT	.234	.095	.214	2.458	.015	.364	2.747
	All_SI	-.018	.040	-.026	-.457	.648	.881	1.135
	All_Tru_ben	-.119	.066	-.141	-1.814	.071	.461	2.169
	All_Tru_int	-.024	.078	-.027	-.308	.758	.365	2.740
	All_Tru_comp	.114	.079	.108	1.443	.150	.495	2.021
	All_PIIT	.253	.054	.301	4.696	.000	.674	1.483

a. Dependent Variable: All_intent

5.2.2.7 Common Method Bias (CMB)

Tests were conducted to determine if CMB was evident, as detailed in Section 4.5.4.3. The total variance extracted by one factor in the Harman's one-factor test for CMB was 30.69%, as outlined in Table 5.3, under the recommended threshold of 50% (Harman, 1967). This one-factor test is the most common method of testing common method bias but flawed (Kock *et al.*, 2021). Bagozzi *et al.* (1991) also suggest examining the factor correlations and if none are above >.90, CMB will not affect the internal consistency of the variables. None of the correlations were higher than 0.79, suggesting CMB is not an influencing factor. Furthermore, as outlined in Section 4.4.4, the survey was designed following the recommendations of MacKenzie and Podsakoff (2012) to minimise bias by including negatively worded items, reverse scales, and giving clear instructions to respondents.

5.2.3 Descriptive Information on Survey Respondents

The descriptive information relating to the respondents is outlined in Table 5.7. In terms of gender, 77% were male, 21% female, with the remaining 2% either non-binary or preferred not to state their gender or self-describe. The respondents varied in age, 41% were aged 18-24, 16% were from the 25-34 age group, 17% were aged between 35-44, 15% were between 45-54, 8% were in the 55-64 age group and 3% were over 65. Respondents also varied with their highest level of education achieved; 34% had a Bachelor degree, 34% had a finished secondary/high school, 11% had a Masters or postgraduate, while 9% had achieved some other form of education such as a 'Green Cert'. 91% of the sample were from Ireland.

Table 5.7 Descriptive Statistics

Gender	Frequency	%
Woman	45	21%
Man	167	77%
Non-binary	1	0%
Prefer to self-describe	2	1%
Prefer not to state	2	1%
Total	**217**	**100%**

Age	Frequency	%
18-24	90	41%
25-34	34	16%
35-44	37	17%
45-54	33	15%
55-64	17	8%
65+	6	3%
Total	**217**	**100%**

Education	Frequency	%
No formal education	3	1%
Primary certificate / Junior School/ Elementary School	7	3%
Secondary certificate / High School	74	34%
Bachelor degree	74	34%
Master degree/Postgraduate	23	11%
PhD	16	7%
Other	20	9%
Total	**217**	**100%**

Country	Frequency	%
Ireland	198	91%
Czech Republic	3	1%
Germany	1	0%
Greece	1	0%
Portugal	1	0%
Spain	3	1%
Sweden	1	0%
UK	4	2%
Other	5	2%
Total	**217**	**100%**

Table 5.8 outlines the relevant demographic details with regards to farming. The majority of respondents had 11-25 years' farming experience (35%), followed by 5-10 years (29%), 19% had over 25 years' experience, while 17% had up to five years' experience. The sample was represented by 39% full-time farmers and 61% part-time farmers. The role on farm was split relatively evenly between Farm Owner (45%) and Farm Employee (43%). There was a reasonable spread of farm size; 32% of respondents indicated a farm size of between 50-100ha, 26% had a farm size of between 100-500ha, 21% of respondents indicated their farm was between 20-50ha, 6% had a farm size of 10-20ha, 6% indicated 2-10ha, 5% had a farm size greater than 500ha and 3% of respondent's farm size was <2ha.

The vast majority of respondents (91%) were involved with a family farm or family company/partnership. Finally, with regard to farm type, single farming was most popular at 59%, while mixed farming was selected by 41% of respondents. Animal-based farming was most popular (Beef 31%, Dairy 29%, Sheep 14%) followed by Cereals & Crops (15%) and Fruit and/or Vegetables (4%).

Table 5.8 Farming Demographic Statistics

Years' experience	Frequency	%
Up to 5 years	37	17%
5-10 years	64	29%
11-25 years	76	35%
Over 25 years	40	18%
Total	**217**	**100%**

Role on farm	Frequency	%
Farm Owner	98	45%
Farm Manager	11	5%
Farm Family Employee	93	43%
Other	15	7%
Total	**217**	**100%**

Type of farm*	Frequency	%
Beef	100	31%
Beekeeping	1	0%
Cereal & Crops	48	15%
Dairy	94	29%
Fruit	6	2%
Pigs	2	1%
Poultry	4	1%
Sheep	45	14%
Vegetables	7	2%
Other	18	6%
	325	**100%**

* more than 1 option allowed

Full Time Vs Part Time Farmer	Frequency	%
Full time	85	39%
Part Time	132	61%
Total	**217**	**100%**

Size of farm	Frequency	%
<2ha	7	3%
Between 2-10 ha	12	6%
Between 10-20 ha	14	6%
Between 20-50 ha	46	21%
Between 50-100 ha	70	32%
Between 100-500 ha	57	26%
>500 ha	11	5%
Total	**217**	100%

Legal status of the farm	Frequency	%
Family farm or family company/partnership	198	91%
Company without family shareholder (i.e., corporation)	6	3%
Cooperative farm (i.e., farmer-owned and run enterprise	9	4%
Other	4	2%
Total	**217**	**100%**

Single vs Mixed farming	Frequency	%
Single farming	129	59%
Mixed farming	88	41%
	217	**100**

Experience with Smart Farming Technology (SFT): Respondents were asked to indicate their level of agreement or disagreement with the statement “I have previous experience of using SFT”. As outlined in Chapter 3, this is a control variable to be assessed. During pilot testing with experts, as discussed in Section 4.4, it was recommended to include this as a Likert scale question rather than a yes/no binary question to suit the SEM process. Table 5.9 outlines that 71% either strongly agreed, agreed, or somewhat agreed with the statement, 9% of the sample were neutral while 20% indicated they strongly disagreed, disagreed, or somewhat disagreed.

Table 5.9 Previous experience of using SFT

I have previous experience of using Smart Farming Technology		
	Frequency	%
Strongly disagree	18	8%
Disagree	14	6%
Somewhat Disagree	12	6%
Neither disagree nor agree	20	9%
Somewhat agree	45	21%
Agree	70	32%
Strongly agree	38	18%
Total	**217**	**100%**

Farm management information systems (FMIS) was the most popular category of SFT used, as indicated by 65% of respondents. This was followed by Precision Agriculture and/or Global Navigation Satellite Systems at 35% and Autonomously Operating Machines at 11% as outlined in Table 5.10. Respondents could indicate experience of using more than one category of technology.

Table 5.10 Category of SFT used

Category of SFT used		
	Frequency	%
None	47	22%
Farm Management Information Systems (e.g., software systems for collecting, processing, and storing data).	142	65%
Precision Agriculture and/or Global Navigation Satellite Systems (e.g., remote sensing technologies, sensors, decision support systems, wireless networks, etc.).	76	35%
Autonomously operating machines (e.g., drones, robotics, machine learning, artificial intelligence, etc.).	23	11%

In terms of when respondents were intending to adopt a particular category of SFT, 40% indicated in the next year, as outlined in Figure 5.2. Approximately 26% of respondents intended to adopt in the next three years, 21% in the next five years, 10% in more than five years and finally 3% said never.

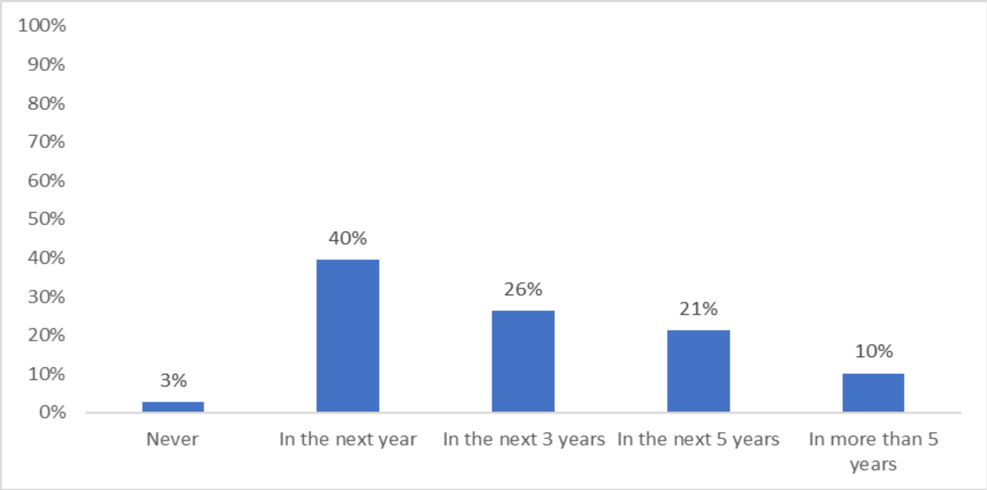

Figure 5.2 Respondents' timeline of intention to adopt

In terms of the category of SFT farmers' intended to adopt, FMIS was most popular at 70%, followed by Precision Agriculture systems at 56% and then autonomously operating machines at 31%. Respondents could indicate more than one category, as per Table 5.11.

Table 5.11 Category of SFT intending to adopt

Category of SFT intending to adopt		
	Frequency	%
None	6	3%
Farm Management Information Systems (e.g., software systems for collecting, processing, and storing data).	152	70%
Precision Agriculture and/or Global Navigation Satellite Systems (e.g., remote sensing technologies, sensors, decision support systems, wireless networks, etc.).	122	56%
Autonomously operating machines (e.g., drones, robotics, machine learning, artificial intelligence, etc.).	68	31%

Incentives and Barriers to adopting SFT: Respondents were asked to rank a series of factors from 1-6 that would encourage them to adopt SFT (1 being most important, and 6 being least important). The values were reverse-coded, and the mean was then calculated. Figure 5.3 illustrates the responses, with 'Technologies that are more straightforward to use' being most important (M = 4.68), followed by 'Financial Assistance' (M = 4.52) and 'Financial Reward' (M = 4.40). 'Specialised education and training' and 'Governmental policies and legislation' were least important, both with a mean value of 2.28, followed by 'Improved digital infrastructure' (M=2.85). An open-ended question allowed respondents to add other factors that they felt were influential. The incentivising factors mentioned mainly included labour savings, better quality of life, environmental benefits, and farmer recommendations. A full list is available in Appendix G.

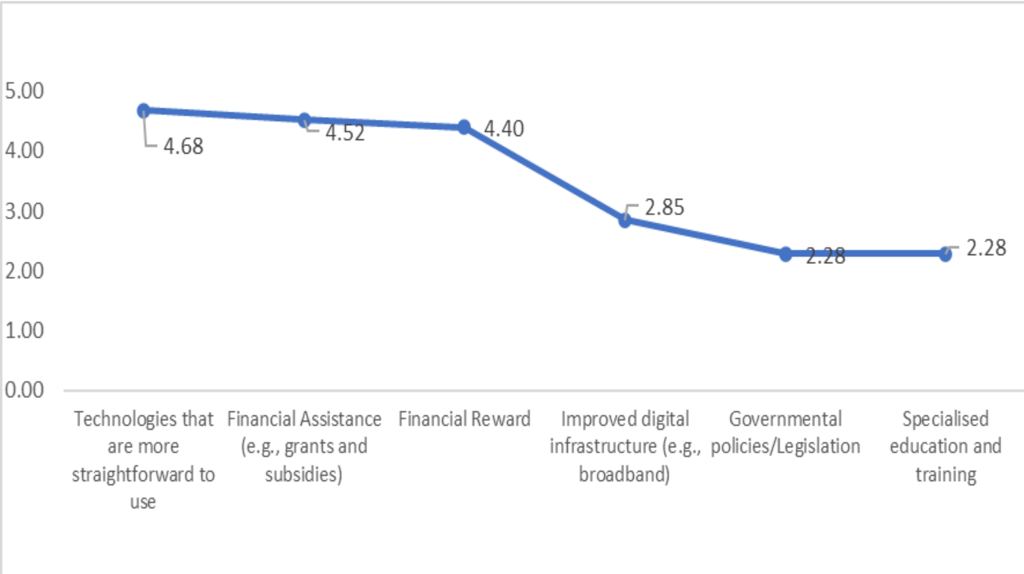

Figure 5.3 Mean values of factors encouraging SFT adoption

Regarding the barriers to adopting SFT, respondents were also asked to rank a series of factors from 1-6 (1 being most important, and 6 being least important). The values were reverse-coded, and the mean calculated, as per Figure 5.4, with 'The cost of buying SFT' coming out clearly as the biggest barrier (M = 5.35). This was followed by 'No clear return on investment' at M = 3.59, 'Lack of technical knowledge' at M = 3.29 and 'Lack of integration of technologies' at M = 3.24. The least important factor was 'Rising costs of inputs' at M = 2.70, followed by 'Data privacy concerns' (M = 2.83). An open-ended question also allowed respondents to add other factors that they felt prevented SFT adoption. The factors mentioned most frequently included the age of the farmer, technology becoming outdated, vendor lock in, and reliability and support from the technology vendors. A full list is available in Appendix G.

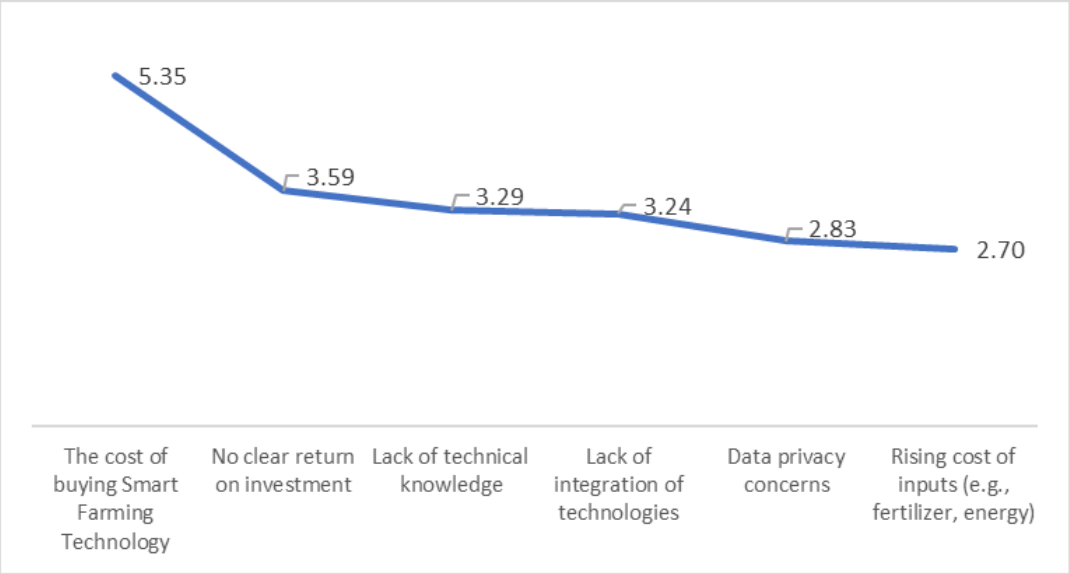

Figure 5.4 Mean values of factors preventing SFT adoption

The actors in the network that influence farmers were also assessed. As outlined in Section 4.4.3, the influence was measured by assessing the people who influence the farmer's behaviour and the farmer's compliance with their thinking. Table 5.12 summarises the findings.

Table 5.12 Influence of farmers' network members on SFT adoption

Statement	n	Agree	Neutral	Disagree
Farmers that I know would think that I should use Smart Farming Technology.	*n=217*	19%	23%	58%
Generally speaking, I want to do what farmers I know think I should do.	*n=217*	48%	27%	25%
My family members would think that I should use Smart Farming Technology.	*n=217*	18%	30%	52%
Generally speaking, I want to do what my family members think I should do.	*n=217*	33%	27%	40%
My farm advisor would think that I should use Smart Farming Technology.	*n=193*	15%	24%	61%
Generally speaking, I want to do my what my farm advisor thinks I should do.	*n=193*	12%	24%	64%
My farm association would think that I should use Smart Farming Technology.	*n=181*	8%	32%	60%
Generally speaking, I want to do what my farm association thinks I should do.	*n=181*	29%	40%	31%
My farm cooperative would think that I should use Smart Farming Technology.	*n=145*	11%	28%	61%
Generally speaking, I want to do what my farm cooperative thinks I should do.	*n=145*	26%	34%	40%

In terms of farm advisors being knowledgeable about SFT, Figure 5.5 below indicates the responses. 75% of respondents either somewhat disagreed, disagreed or strongly disagreed, 22% were neutral while 4% either agreed or somewhat agreed.

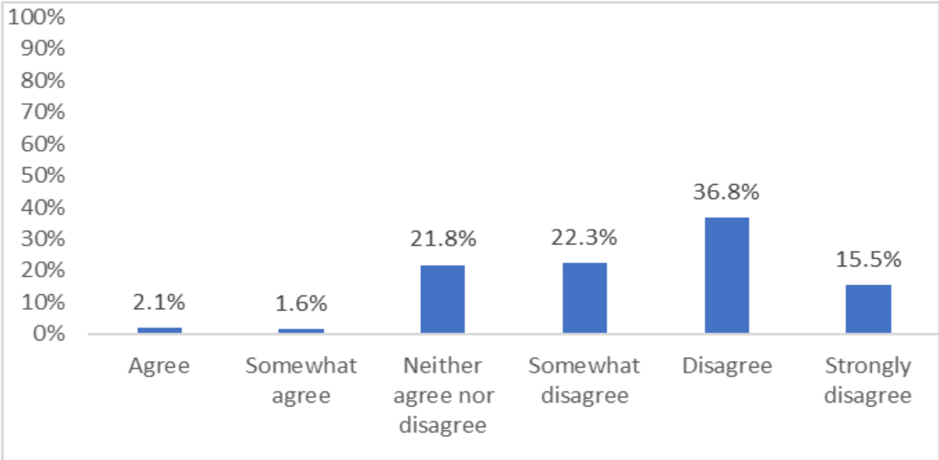

Figure 5.5 Level of agreement/disagreement regarding farm advisors being knowledgeable about SFT

Figure 5.6 outlines the responses to the statement that the farmers' association that the farmer is a member of is knowledgeable about SFT. 51% of respondents either somewhat disagreed, disagreed or strongly disagreed, 32% were neutral while 13% either strongly agreed, agreed or somewhat agreed.

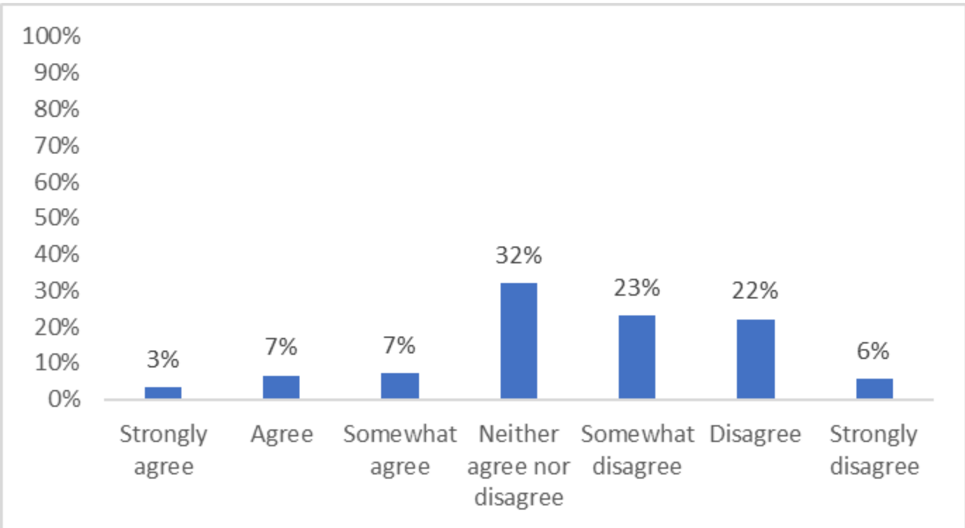

Figure 5.6 Level of agreement/disagreement regarding Farmers' Association being knowledgeable about SFT

Finally, trust in the SFT vendor was measured in terms of the farmer's perception of benevolence, integrity and competency. Overall trusting beliefs not related to the SFT vendor were also captured for descriptive purposes. Figure 5.7 outlines the mean values of the trusting beliefs of SFT vendors and general trusting beliefs. There is no significant difference in the values.

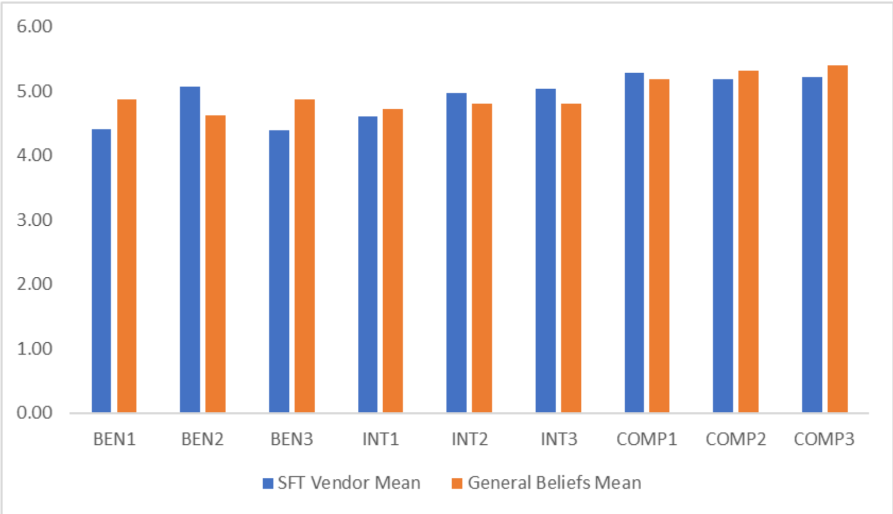

Figure 5.7 Mean values of trusting beliefs of SFT Vendor vs general trusting beliefs

5.3 Reliability and Validity Tests

5.3.1 Reliability Tests

Internal consistency reliability for each factor was assessed using Cronbach's Alpha. As outlined in Table 5.13, all factors achieved a Cronbach's Alpha value of >0.70 and therefore all are reliable (Hair *et al.*, 2019a; Nunnally and Bernstein, 1994). Some items were removed from the constructs PU and ATT to improve reliability. A detailed analysis of the descriptive statistics relating to each of the constructs in the model is provided in Appendix H. As trust is a second order factor, each of the first order elements are also assessed for reliability and validity and achieved a Cronbach's Alpha value of >0.70.

Table 5.13 Results of Cronbach's Alpha for each construct

Scale	No of items	Cronbach's Alpha	Interpretation
Personal Innovativeness in IT (PIIT)	4	0.823	Very Good
Social Influence (SI)	2	0.819	Very Good
Perceived Usefulness (PU)	4*	0.826	Very Good
Perceived Ease of Use (PEOU)	6	0.834	Very Good
Trust - Benevolence (TRU_BEN)	3	0.764	Good

Scale	No of items	Cronbach's Alpha	Interpretation
Trust - Integrity (TRU_INT)	3	0.858	Very Good
Trust - Competency (TRU_COMP)	3	0.886	Very Good
Attitude (ATT)	2*	0.884	Very Good
Behavioural Intention (INT)	2	0.724	Good

*Items removed to improve Cronbach's Alpha

Assessing the composite reliability (CR) as outlined in Table 5.14 confirms that all constructs score above 0.60, as recommended by Bagozzi and Yi (1988), confirming that all measures are reliable and consistent.

Table 5.14 CR for all constructs

Construct	CR
SI	0.654
PU	0.834
PEOU	0.844
ATT	0.887
PIIT	0.835
INTENT	0.738
TRU_BEN	0.763
TRU_INT	0.864
TRU_COM	0.887

As the model contains a second-order latent factor, trust, comprising three first-order latent factors, namely Integrity, Benevolence and Competency, tests were run with the second order factor and also using the individual trust items as first order factors to ensure reliability and validity. CR is confirmed for all first-order latent factors, with values >.60. This process is recommended by Chen *et al.* (2005) and Koufteros *et al.* (2009).

5.3.2 Validity Tests

Validity tests relating to the model constructs were conducted following a review of the descriptives tests. Face validity was determined through expert reviews and pre-testing, as outlined in Section 4.4.4. Convergent validity (CV) was assessed using the factor loadings and the average variance extracted (AVE). Factor loadings, which express the relationship of each item to the construct, are all above 0.40, as recommended by Hair *et al.* (2019c) for sample sizes >200. All factor loadings are provided in Appendix H and I. AVE values greater than 0.50 are deemed acceptable to determine CV. Results in Table 5.15, highlighted an issue with the AVE of PEOU <.50. Testing to achieve an AVE >.50

was conducted by removing items with the lowest factor loadings. Following analysis, three items were removed, namely PEOU2, PEOU4 and PEOU5.

Table 5.15 AVE scores for each factor

	CR	AVE
SI	0.654	0.654
PU	0.834	0.560
PEOU	0.844	0.485
ATT	0.887	0.797
PIIT	0.835	0.559
INTENT	0.738	0.589
TRU_BEN	0.763	0.518
TRU_INT	0.864	0.679
TRU_COM	0.887	0.724

This resulted in the AVE for PEOU achieving a value >0.50, as outlined in Table 5.16. Cronbach's Alpha was rested following the removal of items in PEOU, as demonstrated in Appendix I. A value above >0.70 was achieved, as demonstrated in Appendix H and I, determining no issues with reliability or validity.

Table 5.16 Final AVE scores for each factor

	CR	AVE
SI	0.654	0.654
PU	0.834	0.559
PEOU	0.855	0.664
ATT	0.888	0.798
PIIT	0.834	0.559
INTENT	0.738	0.588
TRU_BEN	0.763	0.518
TRU_INT	0.864	0.679
TRU_COM	0.888	0.725

Discriminant validity was assessed using the Fornell and Larcker (1981) method which stipulates that the square root of AVE of each latent variable should be greater than the inter-construct correlation. This compares the square root of the AVE on the diagonal, with the correlation coefficients on the off diagonal for each construct in the relevant rows and columns. Analysis displayed an issue with the DV for PU, and first order factors for trust, namely Integrity and Benevolence, as outlined in Table 5.17.

Table 5.17 Discriminant Validity using Trust first order factors

	CR	AVE	MSV	MaxR(H)	TRU_INT	SI	PU	PEOU	ATT	PIIT	INTENT	TRU_BEN	TRU_COM
TRU_INT	0.864	0.679	0.796	0.867	**0.824**								
SI	0.654	0.654	0.142	0.654	0.228	**0.809**							
PU	0.834	0.559	0.624	0.852	0.344								
PEOU	0.855	0.664	0.453	0.865	0.220	0.246	0.497						
ATT	0.888	0.798	0.624	0.905	0.311	0.377	0.790	0.487					
PIIT	0.834	0.559	0.453	0.843	0.207	0.168	0.488	0.673	0.534				
INTENT	0.738	0.588	0.569	0.779	0.185	0.226	0.754	0.533	0.732	0.646			
TRU_BEN	0.763	0.518	0.796	0.766	0.892	0.142	0.303	0.235	0.226	0.245	0.096		
TRU_COM	0.888	0.725	0.587	0.890	0.766	0.232	0.404	0.224	0.393	0.211	0.278	0.681	

As BEN1 had the lowest factor loading, this was firstly removed but resulted in an issue with convergent reliability. Upon further testing, the total removal of the first-order factor Benevolence with Integrity and Competency remaining, enabled DV to be achieved for Trust factors. For PU, item 6 was removed as this had the lowest factor loading. Removal of the item resulted in DV for PU and indeed all constructs being achieved, as outlined in Table 5.18. Cronbach's Alpha for PU was retested and achieved a value of >.70, as illustrated in Appendix H and I.

Table 5.18 Discriminant Validity for Trust first order factors without Benevolence

	CR	AVE	MSV	MaxR(H)	SI	PU	PEOU	ATT	PIIT	INTENT	TRU_INT	TRU_COM
SI	0.823	0.700	0.142	0.829	**0.837**							
PU	0.828	0.618	0.595	0.843	0.302***	**0.786**						
PEOU	0.856	0.665	0.454	0.865	0.247**	0.477***	**0.815**					
ATT	0.888	0.798	0.595	0.910	0.377***	0.771***	0.484***	**0.894**				
PIIT	0.834	0.558	0.454	0.844	0.168*	0.474***	0.674***	0.534***	**0.747**			
INTENT	0.740	0.591	0.529	0.787	0.226**	0.715***	0.531***	0.727***	0.645***	**0.769**		
TRU_INT	0.862	0.675	0.619	0.863	0.236**	0.340***	0.225**	0.324***	0.200*	0.201*	**0.822**	
TRU_COM	0.887	0.724	0.619	0.891	0.233**	0.389***	0.223**	0.392***	0.211**	0.276**	0.787***	**0.851**

Significance of Correlations: * p < 0.050 ** p < 0.010 *** p < 0.001

DV using the second order factor Trust, comprising of Integrity and Competency is also achieved and outlined in Table 5.19 below.

Table 5.19 Discriminant Validity Test using Fornell and Lacker method

	CR	AVE	MSV	MaxR(H)	SI	PU	PEOU	ATT	PIIT	INTENT	Trust
SI	0.823	0.700	0.142	0.829	**0.837**						
PU	0.828	0.618	0.595	0.843	0.302***	**0.786**					
PEOU	0.856	0.665	0.454	0.865	0.247**	0.477***	**0.815**				
ATT	0.888	0.798	0.595	0.910	0.376***	0.771***	0.484***	**0.894**			
PIIT	0.834	0.558	0.454	0.844	0.168*	0.474***	0.674***	0.534***	**0.747**		
INTENT	0.740	0.592	0.527	0.789	0.226**	0.714***	0.531***	0.726***	0.644***	**0.769**	
Trust	0.885	0.794	0.169	0.910	0.257**	0.412***	0.247**	0.408***	0.229**	0.278**	**0.891**

Significance of Correlations: * p < 0.050 ** p < 0.010 *** p < 0.001

Furthermore, discriminant validity was tested using the Heterotrait-Monotrait ratio of correlations (HTMT). Thresholds are below 0.850 for strict and >0.900 for liberal discriminant validity (Henseler *et al.*, 2014). All values were below 0.850, as illustrated in Table 5.20.

Table 5.20 HTMT Analysis

	SI	PU	PEOU	ATT	PIIT	INTENT	Trust
SI							
PU	0.236						
PEOU	0.211	0.407					
ATT	0.313	0.672	0.434				
PIIT	0.135	0.392	0.572	0.451			
INTENT	0.169	0.570	0.416	0.585	0.495		
Trust	0.206	0.340	0.221	0.344	0.191	0.211	

5.4 Examining Model Constructs

This section details the analysis of each of the constructs used in the statistical model. Figure 5.8 illustrates the first and second order latent variables input into AMOS. These latent variables relate to the hypotheses outlined in Chapter 3. Items were removed when assessing reliability and validity, as detailed in Section 5.3 and Appendix I.

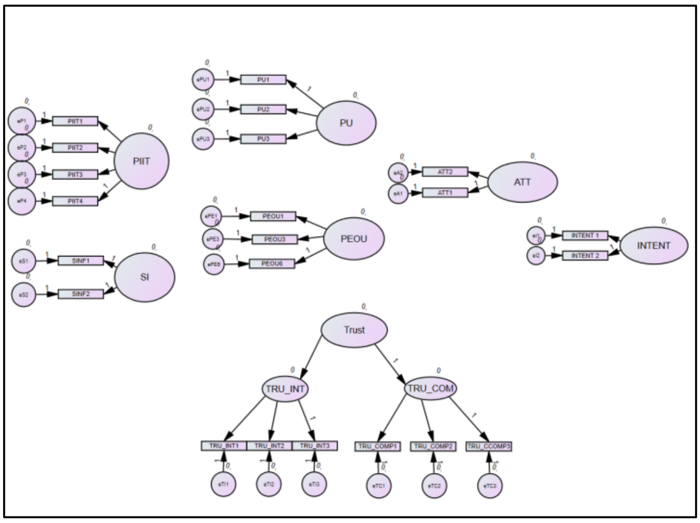

Figure 5.8 Latent Variables

Each construct was measured with multiple items, as indicated by literature. All questions were structured using a 7-point Likert scale where 1= Strongly Disagree, 7= Strongly Agree. As indicated in Section 4.4.4, this order was reversed for questions related to social influences. The mean values of each variable construct were calculated using SPSS. This allows for a measure of central tendency to indicate the average response of participants.

5.5 Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) was conducted using SPSS AMOS 28.0.0. As outlined, the model contains a second-order factor, trust in the SFT vendor. The model was initially tested using only the first-order factors to ensure that there were no issues with CV and DV. As outlined in Section 5.3.1, one first-order factor in trust (Benevolence) was dropped as result. The complete model with the second order factor, Trust, using two first-order factors was then tested and showed no reliability or validity concerns. This model was presented for CFA. Hair *et al.* (2010) determine that three criteria should be considered to determine the appropriateness of the measurement model; 1.) assessment of model fit, 2.) significance of parameter estimates, and 3.) reliability and validity. Reliability and validity have been confirmed. as outlined in Section 5.3.1 and 5.3.2, while the following sections discuss assessment of model fit and significance of parameter estimates.

5.5.1 Assessment of model fit

With CFA, it is recommended that the first step is examination of the measurement model to determine validity and data fit. Determining these measures indicates the performance of the model when reproducing the observed covariance matrix among the indicators (Hair *et al.*, 2019a). The threshold for each of the measures is outlined in Table 5.21.

Table 5.21 Characteristics of different fit indices demonstrating goodness of fit

Measure	Poor	Acceptable	Excellent
CMIN/DF	> 5	> 3	> 1
CFI	<0.90	<0.95	>0.95
SRMR	>0.10	>0.08	<0.08
RMSEA	>0.08	>0.06	<0.06
PClose	<0.01	<0.05	>0.05

Adapted from Hu and Bentler (1999) and Byrne (2010)

The model fit indices and its interpretation is presented in Table 5.22, indicating that the overall measurement model is a good fit. The Baseline Comparisons and Parsimony-

Adjusted Measures in Model Fit Results are within the recommended thresholds of >.90 for IFI and TLI (Hair *et al*., 2005). For the PNFI value, as discussed in Section 4.5.4.2.3, tests were conducted to determine model parsimony with alternative models. This is outlined in greater detail in Section 5.6.1.

Table 5.22 Model Fit Indices for the Measurement Model

Measure	Fit indices	Threshold	Interpretation
CMIN/DF	1.329	Between 1 and 3	Excellent
CFI	0.977	>0.95	Excellent
SRMR	0.043	>0.03 < 0.09	Excellent
IFI	0.977	>.90	Excellent
TLI	0.971	>.90	Excellent
RMSEA	0.039	< 0.06	Excellent
PClose	0.926	> 0.05	Excellent

5.5.2 Modification Indices

The Modification Indices (MI) were consulted to determine if adjustments should be made to the model to result in further improvement. As recommended by Hair *et al.* (2019a) the MI for each variable's error terms should be assessed first. However, as outlined by Collier (2020) caution should be taken to not draw all suggested covariances and error terms should only be covaried across the same constructs. On analysis of the MI covariances, only two appropriate changes were suggested, as outlined in Table 5.23. The full output is available in Appendix J.

Table 5.23 Error Term Modification Indices

			M.I.	Par Change
eTI2	<-->	eTI1	12.002	0.138
eP1	<-->	eP2	4.207	0.118

This resulted in a slightly better model fit, as outlined in Table 5.24.

Table 5.24 Fit Indices -CFA Model comparison

Fit Measure	Chi Square	Df	X^2/Df	SRMR	CFI	IFI	TLI	PNFI	RMSEA	Pclose
			>1<3	>0.03 < 0.09	>0.95	>0.90	>0.90	>.50	<0.06	>0.05
CFA Model 1	248.558	187	1.329	0.430	0.977	0.977	0.971	0.739	0.039	0.926
CFA Model 2	216.81	185	1.172	0.411	0.988	0.988	0.985	0.740	0.028	0.996

The standardised residual covariances were then assessed. Segars and Grover (1993) outline that a standardised residual can be considered large if it is above 2.58 in absolute value. However, Hair *et al.* (2019a) suggest values greater than 4.00 are an unacceptable degree of error. On analysis of the table in Appendix J no items displayed values above the cut off value of 2.58. Based on the original model fit results, the CFA Model 2, as outlined in Figure 5.9, is suitable for structural equation modelling. The AMOS results for the CFA Model 2 are provided in Appendix K.

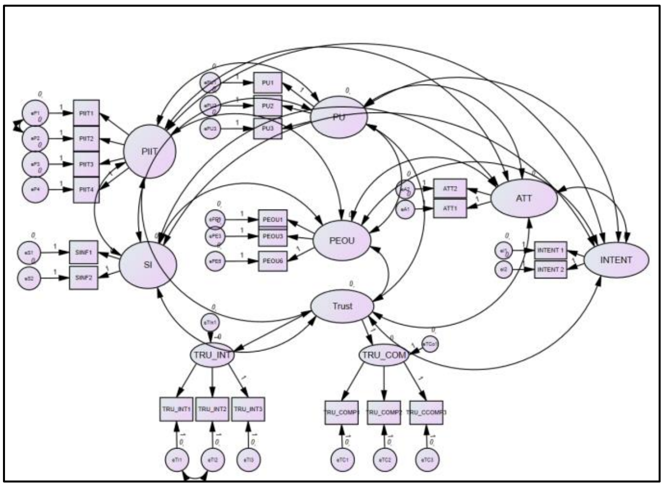

Figure 5.9 Proposed Measurement model

5.5.3 Nomological Validity

Nomological validity testing, as presented in Table 5.25, outlines the correlations and the covariances for the model. Only hypothesised relationships are displayed. As outlined in Section 4.5.4, nomological validity assesses if the model is theoretically valid (Lee, 2019). All correlations displayed are positive and all items are significant at p = *** except for the relationship between PEOU and trust (p= 0.003) which is still significant at ** p <.01. The claim of nomological validity can be assumed as the correlations are consistent with the hypothesised model.

Table 5.25 Nomological Validity Testing

Correlations				**Covariances**			
			Estimate	**Estimate**	**S.E.**	**C.R.**	**P**
SI	<-->	PU	0.302	0.24	0.069	3.482	***
PEOU	<-->	PIIT	0.683	0.792	0.115	6.867	***
PIIT	<-->	INTENT	0.651	0.589	0.09	6.558	***
PU	<-->	PIIT	0.478	0.341	0.068	4.997	***
PU	<-->	PEOU	0.477	0.346	0.068	5.066	***
PU	<-->	ATT	0.771	0.398	0.059	6.734	***
PU	<-->	INTENT	0.714	0.404	0.062	6.477	***
PEOU	<-->	ATT	0.484	0.405	0.074	5.479	***
Trust	<-->	PEOU	0.243	0.205	0.07	2.931	0.003

Correlations					Covariances		
Trust	<-->	ATT	0.406	0.243	0.053	4.599	***
Trust	<-->	PU	0.412	0.214	0.049	4.388	***
ATT	<-->	INTENT	0.726	0.475	0.066	7.141	***

Note: *p <.05, **p <.01, ***p <0.001

5.5.4 Power of the Study

Following the CFA model analysis, (specifically Df=216.81, RMSEA=0.028, RMSEA (null)=0.229, N=217), the model power was calculated using the Preacher and Coffman (2006) tool. A figure of 1.00 was achieved which deems the model power acceptable (Cohen, 1988).

5.6 Structural Equation Modelling (SEM)

In this section, the analysis of the structural model which represents the hypothesised relationships between the latent variables is discussed. Figure 5.10 illustrates the model with the hypothesised relationships.

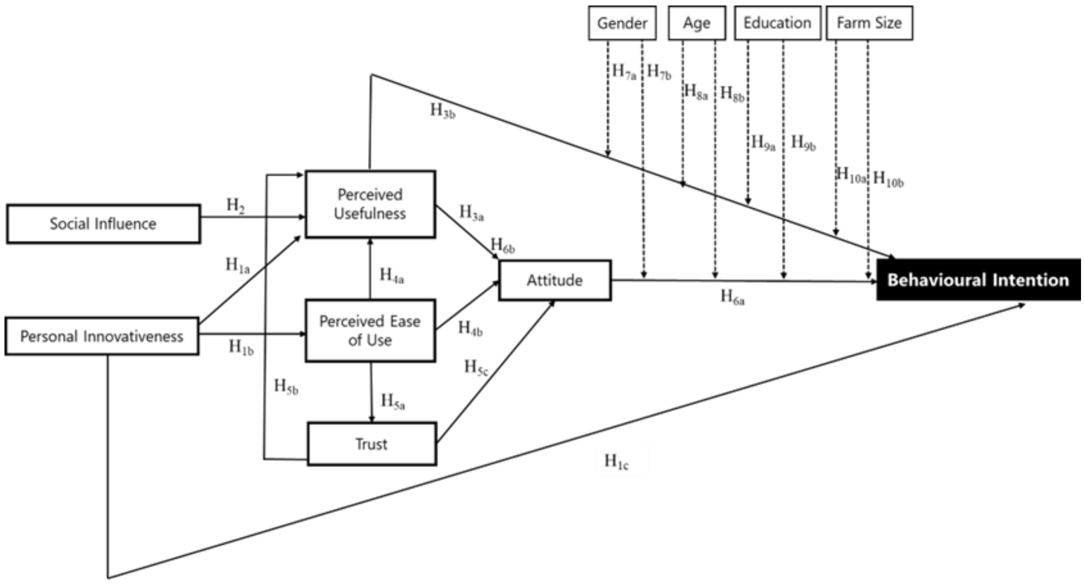

Figure 5.10 Hypothesised Model

5.6.1 Initial Model Fit and Nested Models

To validate the hypotheses, the first step is retesting the model with the causal relationships and control variable (SFT experience) in place. This will determine if the model fit is still acceptable (Hair *et al.*, 2019a). The AMOS analysis on this initial model version (SEM Model 1) produced the following fit indices, (X^2= 275.527, Df=211, X^2/Df=1.306, SRMR=0.0588 and RMSEA=0.038 with PClose=0.958). This demonstrates that model fit is good (Byrne, 2010) and no further model adjustments were necessary Furthermore, the controlling effect of SFT experience was found to be significant (p<.05).

Next, the Chi-square difference test was used to compare nested models with the hypothesised model. Models are said to be nested once the parameters estimated in the restricted model are a subset of the parameters in the model which is less restrictive (Melas *et al.*, 2011). The first nested model (SEM Model 2) tested the implied null-hypotheses which implied that SI was mediated by PU, PIIT mediated by PU and PEOU, PEOU mediated by attitude and trust mediated by attitude. Direct paths were added in the structural model between SI and behavioural intention, Trust and behavioural intention and PEOU and behavioural intention. The path between PIIT and BI already existed. The Chi-square difference test showed that the model fit was statistically different, as outlined in Appendix L. Furthermore, the fit indices, as outlined in Table 5.26, highlighted a worse model fit. Specifically, the SRMR was >0.09, CFI value was < 0.95, RMSEA was <.06 and the Pclose value was <0.05 and therefore this model was rejected.

The next nested model (SEM Model 3) constrained the direct paths from PIIT to PU and PEOU and SI to PU to zero, thus essentially removing the effect of these external variables. The Chi-square difference test demonstrated there was a significant difference in the model fit between Model 3 and Model 1. The fit indices were then assessed which showed a worse model fit, as outlined in Table 5.26. In particular, the SRMR value was >.09. This model was also rejected.

The final nested model (SEM Model 4) tested the assumption that all relationships with the behavioural intention to adopt SFT are mediated, and therefore no direct relationships exist. All direct paths to BI were constrained to zero, except for the path between attitude and BI. The model fit also reduced slightly for this nested model as demonstrated by the Chi-square difference test and the fit indices.

Table 5.26 Nested Model Tests and Fit Indices

Fit Measure	**Chi Squar**	**Df**	**X^2/Df**	**SRMR**	**CFI**	**IFI**	**TLI**	**PNFI**	**RMSEA**	**Pclose**	**AIC**
			>1<3	**>0.03 < 0.09**	**>0.95**	**>0.90**	**>0.90**	**>.50**	**<0.06**	**>0.05**	
SEM Model 1	275.527	211	1.306	0.0588	0.976	0.976	0.971	0.756	0.038	0.958	405.527
SEM Model 2	397.000	213	1.864	**0.1612**	**0.932**	0.933	0.919	0.728	**0.063**	**0.014**	523.000
SEM Model 3	328.482	214	1.535	**0.0968**	0.957	0.958	0.950	0.751	0.050	0.503	452.482
SEM Model 4	295.492	213	1.387	0.0630	0.969	0.970	0.964	0.757	0.042	0.864	421.492

As outlined above, SEM Model 1 has the best model fit so was retained. Furthermore, the original TAM was tested for comparison purposes, removing the variables associated with this study (i.e. personal innovativeness, social influence, trust). Original TAM also delivered a worse model fit (X^2=107.759 Df=39, X^2/Df=2.7613, SRMR=0.1914 and RMSEA=.090 with PClose=0.001).

5.6.2 Mediation Tests

The hypothesised model presents multiple mediation paths. As a result, multiple regression tests were conducted in SPSS, using a bootstrapping approach, to assess the significance of the indirect effects. Each of these relationships were examined for statistical significance in order to deliver the most suitable model to allow verification of the proposed hypothesis at varying levels of the mediator. Full details of all the regression tests conducted are available in Appendix M.

All the proposed mediation paths in the original hypothesised model are statistically significant and indicate partial mediation. Tables 5.27-5.32 display the mediation results and Figures 5.11-5.16 outline a graphical representation of the mediation.

Table 5.27 PIIT to PU, mediated by PEOU

Path Test	β	t	p	Significant	CI
PIIT - PU	0.3084	(215)=6.1282	0.0000***	Y	
PIIT - PEOU	0.5900	(215)=10.4103	0.0000***	Y	
PEOU - PU	0.2114	(215)=3.5863	0.0004**	Y	
Bootstrapped bias-corrected confidence (M = PEOU)	0.1247				0.0480 to 0.2108
Direct Effect: PIIT - PU, controlling for M	0.1836	(215)=3.0567	0.0025**	Y	
Mediation Confirmed?	Y				
Mediation Type	Partial				

Note: *p <.05, **p <.01, ***p <0.001

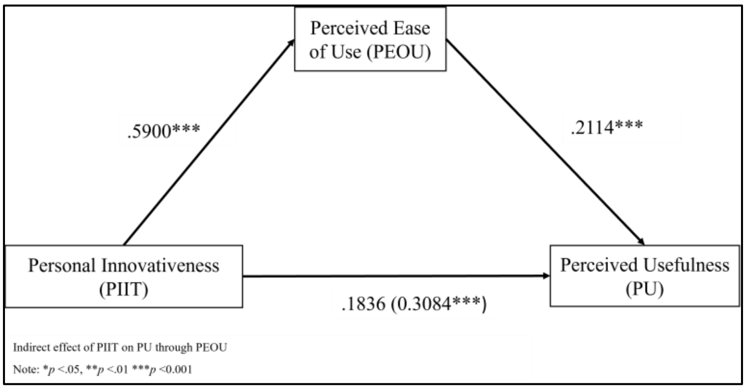

Figure 5.11 PIIT to PU, mediated by PEOU

As outlined above in Table 5.27 and Figure 5.11, PEOU partially mediates the relationship between PIIT and PU.

Table 5.28 PIIT to BI, mediated by PU

Path Test	β	t	p	Significant	CI
PIIT - BI	0.4080	(215)=8.1320	0.0000***	Y	
PIIT - PU	0.3084	(215)=6.1282	0.0000***	Y	
PU - BI	0.4698	(215)=7.8157	0.0000***	Y	
Bootstrapped bias-corrected confidence (M = PU)	0.1449				0.0876 to 0.2106
Direct Effect: PIIT - BI, controlling for M	0.2631	(215)=5.4731	0.0000***	Y	
Mediation Confirmed?	Y				
Mediation Type	Partial				

Note: **p* <.05, ***p* <.01, ****p* <0.001

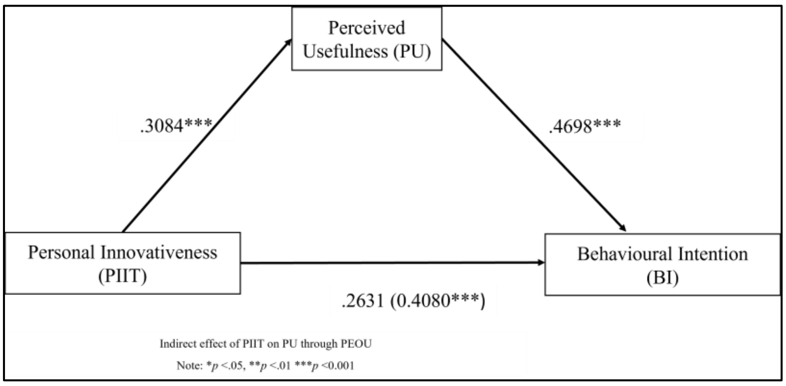

Figure 5.12 PIIT to BI, mediated by PU

As outlined above in Table 5.28 and Figure 5.12, PU partially mediates the relationship between PIIT and BI.

Table 5.29 PEOU to PU, mediated by Trust

Path Test	β	t	p	Significant	CI
PEOU-PU	0.3157	(215)=6.4446	0.0000***	Y	
PEOU-Trust	0.1664	(215)=3.2017	0.0016**	Y	
Trust-PU	0.2639	(215)=4.2663	0.0000***	Y	
Bootstrapped bias-corrected confidence (M = Trust)	0.0439				0.0119 to 0.0905
Direct Effect: PEOU- PU, controlling for M	0.2718	(215)= 5.6332	0.0000***	Y	
Mediation Confirmed?	Y				
Mediation Type	Partial				

Note: *p <.05, **p <.01, ***p <0.001

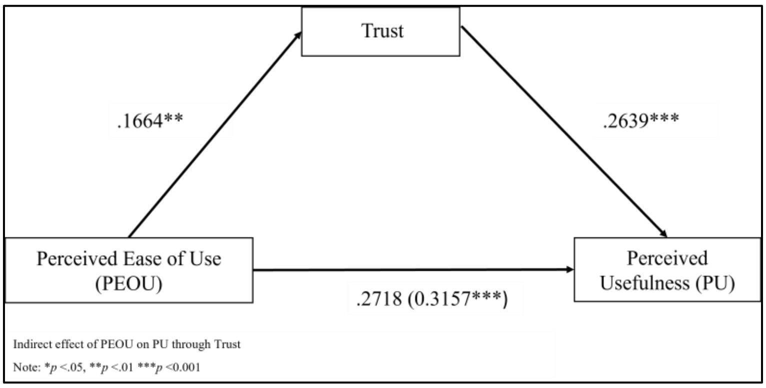

Figure 5.13 PEOU to PU, mediated by Trust

Table 5.29 and Figure 5.13 demonstrates that trust partially mediates the relationship between PEOU and PU.

Table 5.30 PEOU to ATT, mediated by Trust

Path Test	β	t	p	Significant	CI
PEOU-ATT	0.3258	(215)=7.0391	0.0000***	Y	
PEOU-Trust	0.1664	(215)=3.2017	0.0016**	Y	
Trust-ATT	0.2914	(215)=5.0649	0.0000***	Y	
Bootstrapped bias-corrected confidence (M = Trust)	0.0485				0.0123 to 0.0973
Direct Effect: PEOU- ATT, controlling for M	0.2773	(215)=6.1801	0.0000***	Y	
Mediation Confirmed?	Y				
Mediation Type	Partial				

Note: *p <.05, **p <.01, ***p <0.001

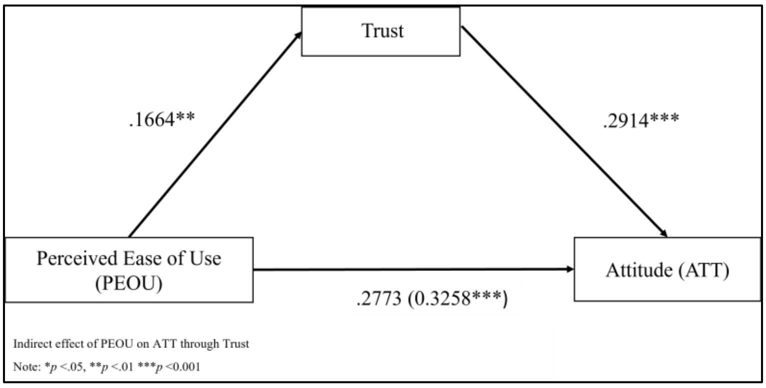

Figure 5.14 PEOU to ATT, mediated by Trust

As presented in Table 5.30 and Figure 5.14, trust serves as a partial mediator in the relationship between PEOU and attitude.

Table 5.31 Trust - ATT, mediated by PU

Path Test	β	t	p	Significant	CI
Trust-ATT	0.3672	(215)=6.0327	0.000***	Y	
Trust-PU	0.3383	(215)=5.2352	0.000***	Y	
PU-ATT	0.6019	(215)=12.1480	0.000***	Y	
Bootstrapped bias-corrected confidence (M = PU)	0.0485				0.1148 to 0.2996
Direct Effect: Trust-ATT, controlling for M	0.1636	(215)=3.2830	0.0012**	Y	
Mediation Confirmed?	Y				
Mediation Type	Partial				

Note: *p <.05, **p <.01, ***p <0.001

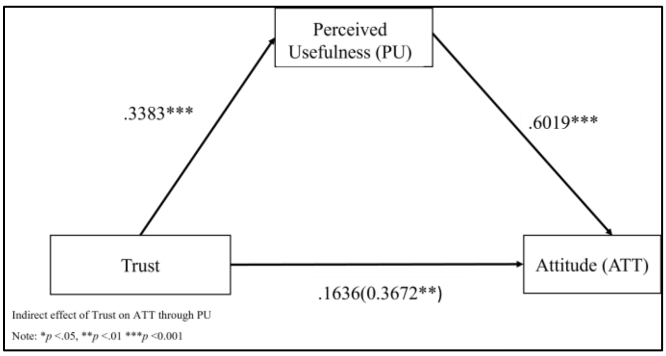

Figure 5.15 Trust - ATT, mediated by PU

Table 5.31 and Figure 5.15 outline that PU acts as a partial mediator in the relationship between trust and attitude.

Table 5.32 PU – BI, mediated by ATT

Path Test	β	t	p	Significant	CI
PU - BI	0.5967	(215)=10.0996	0.0000	Y	
PU - ATT	0.6566	(215)=13.7618	0.0000	Y	
ATT - BI	0.3831	(215)=4.7597	0.0000	Y	
Bootstrapped bias-corrected confidence (M = ATT)	0.2516				0.1404 to 0.3686
Direct Effect: PU - BI, controlling for M	0.3451	(215)=4.4689	0.0000	Y	
Mediation Confirmed?	Y				
Mediation Type	Partial				

Note: **p* <.05, ***p* <.01, ****p* <0.001

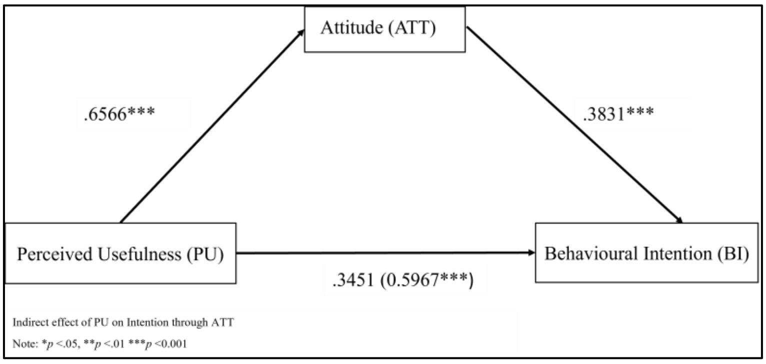

Figure 5.16 PU - BI, mediated by ATT

Finally, Figure 5.16 and Table 5.32 demonstrate that attitude serves as a partial mediator in the relationship between PU and BI. As all mediation paths were indicated as partial, no changes to the paths in the model were needed. The next step in the SEM process is to consider alternative theories which are outlined in Section 5.6.3 below.

5.6.3 Alternative Theories

In addition to the nested model testing and mediation analysis, several alternative theories were tested to further ensure model fit. Table 5.33 shows the model fit comparisons for the alternative theories.

5.6.3.1 Theory 1 – Relationship between Trust and PU

The relationships between PU, PEOU and trust are conflicted in the literature. Several authors suggest that PEOU is an antecedent to trust while trust then impacts PU (Gefen *et al.*, 2003; Pavlou, 2003; Wu and Chen, 2005). However, as outlined in Section 3.3.5, Dhagarra *et al*. (2020), Amin *et al.* (2014) and Roca *et al.* (2009) stipulate that PU affects trust. Accordingly, a version of SEM Model 1 was created where both PU and PEOU influence trust. When this relationship is changed, the model fit (SEM Model 5) improves, as demonstrated in the results (X^2= 270.380 Df=211, X^2/Df=1.281, SRMR=0.0570 and RMSEA=0.036 with PClose=0.973). Furthermore, the value for CFI increases slightly from 0.976 to 0.978 and the AIC value is lower (405.527 vs 400.380). Therefore, based on examination, SEM Model 5 is saved for further analysis.

5.6.3.2 Theory 2 – Removal of Attitude

The original TAM model devised by Davis (1986) included attitude as a variable, as discussed in Section 3.3.6. However, when the final revision of the model was complete, attitude was removed to deliver a more parsimonious model. The role that attitude plays on BI is conflicted in the literature. Several authors determine that attitude has a mediating effect on BI (Agarwal and Prasad, 1999; Shang et al., 2021; Yousafzai et al., 2007a), while others suggest there is no relationship between attitude and BI (Nistor and Heymann, 2010; Teo, 2009). Accordingly, a version (SEM Model 6) of SEM Model 5 was created where attitude was removed, and a direct path was created from PEOU - BI. The path between PU and BI already exists. Table 5.34 outlines the model fit indices and shows a slightly better model fit for this SEM Model 6 (X^2= 219.006 Df=173, X^2/Df=1.266, SRMR=0.0515 and RMSEA=0.035 with PClose=0.967). Parsimony indices were consulted, and the AIC value was lower for SEM Model 6. Therefore, SEM Model 6 is retained for further analysis.

5.6.3.3 Theory 3 – Personal Innovativeness as a moderator

As outlined in Section 3.3.1, Dabholkar and Bagozzi (2002) determine that individual traits can act as moderators rather than having a direct effect on a variable. Certainly, Agarwal and Prasad (1998) hypothesised that PIIT can act as a moderator. However, their study outlined that only slight moderation was observed between compatibility and intention, and there was no moderating influence on PU, PEOU or usage intentions. Alkawsi *et al.* (2021) also hypothesised that PIIT has a moderating influence on the relationship between performance expectancy, which can be likened to PU, and behavioural intention. However, this relationship was not supported. Jeong and Choi (2022) also hypothesised that PIIT would moderate the relationship between relative advantage and intention, but again this was not supported. Nevertheless, Cheng (2014) found empirical support that PIIT moderates the relationships between PU and intention in consumers' adoption of mobile learning. Consequently, a version of model SEM Model 6 was created where PIIT was removed as an antecedent and instead acts a moderator between PU and behavioural intention. A latent interaction variable representing PU and PIIT was created and tested. This model (SEM Model 7) resulted in a worse model fit (X^2= 200.222, Df=122, X^2/Df=1.641 SRMR=0.0881 and RMSEA=0.054 with PClose=0.283 and AIC=298.222). Although AIC is lower indicating a more parsimonious model, the model fit indices for SEM Model 6 are still better. Therefore, SEM Model 7 is rejected and PIIT is retained as an antecedent.

Table 5.33 illustrates the model fit analysis between alternative models and demonstrates that SEM Model 6 is the best fit.

Table 5.33 Alternative Theories Model fit analysis

Fit Measure	Chi Square	Df	X^2/Df	SRMR	CFI	IFI	TLI	PNFI	RMSEA	Pclose	AIC
			>1<3	>0.03 < 0.09	>0.95	>0.90	>0.90	>.50	<0.06	>0.05	
SEM Model 1	275.527	211	1.306	0.0588	0.976	0.976	0.971	0.756	0.038	0.958	405.527
SEM Model 5	270.380	211	1.281	0.0570	0.978	0.978	0.973	0.757	0.036	0.973	400.380
SEM Model 6	219.006	173	1.266	0.0515	0.980	0.980	0.976	0.752	0.035	0.967	335.006
SEM Model 7	200.222	122	1.641	0.0881	0.958	0.959	0.947	0.718	0.054	0.283	298.222

The final step in the initial structural model analysis was to remove any non-significant paths (p>.05 and C.R.<1.95) from SEM Model 6 and reassess the model fit. As a result, the model fit decreased very slightly (X^2=200.222, Df=176, X^2/Df=1.265, SRMR=0.0555, RMSEA=0.035 with PClose=0.967, IFI=0.9681, CFI=0.981, TLI=0.976, PNFI=0.763). Therefore, SEM Model 6, outlined in Figure 5.17 is still retained for hypotheses verification.

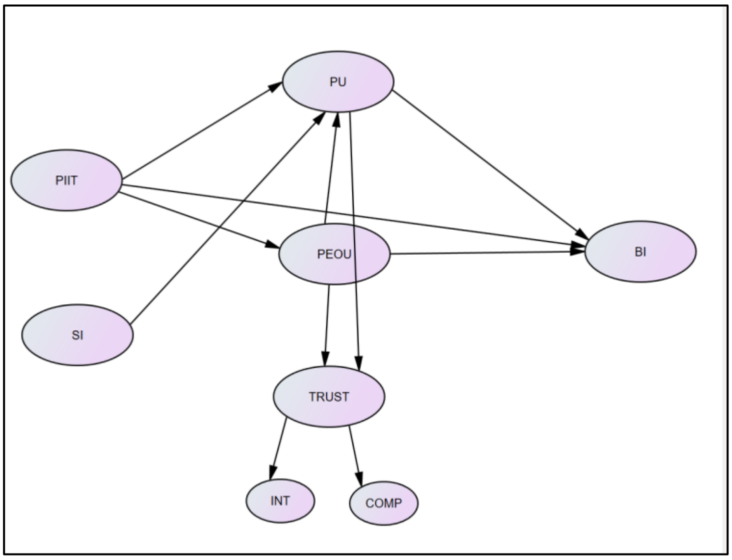

Figure 5.17 Final Structural Model (SEM Model 6)

5.6.4 Moderation Tests

Moderation testing was conducted, as detailed in Section 4.5.5.4. The results of each moderation test are presented below, indicating the significance of moderation between the predictor variables and the dependent variable. Further analysis of each moderation test result is presented in Appendix N. The moderation tests examined the relationship between PU and behavioural intention, moderated by age, gender, education and farm size. The original model also suggested that the relationship between attitude and behavioural intention was moderated by age, gender, education, and farm size. However, during the model testing, attitude was removed from the model to deliver a better model fit. Therefore, these hypothesised relationships were not tested

Table 5.34 PU to Intent, moderated by Age

Dependent Variable: Behavioural Intention	Predictors	Interaction Term	R2	ΔR^2 change	F	p	Significance
Main Effects Model	Age, PU		0.319		F(2,214)= 51.619	0.000	Y
Interaction Effects Model		Age*PU		0.018	ΔF(1,213) =5.717	0.018	Y*

**indicates moderation is observed*

Table 5.34 suggests that age moderates the relationship between PU and behavioural intention.

Table 5.35 PU to Intent, moderated by Gender

Dependent Variable: Behavioural Intention	Predictors	Interaction Term	R2	ΔR^2	F	p	Significance
Main Effects Model	Gender, PU		0.328		F (2, 214) =53.606	0.000	Y
Interaction Effects Model		Gender*PU		0.0000	ΔF (1,213) =0.01	0.973	N

As outlined in Table 5.35, gender does not moderate the relationship between PU and behavioural intention.

Table 5.36 PU to Intent, moderated by Education

Dependent Variable: Behavioural Intention	Predictors	Interaction Term	R2	ΔR^2	F	p	Significance
Main Effects Model	Education, PU		0.319		F (2,214) =51.702	0.000	Y
Interaction Effects Model		Education*PU		0.003	ΔF(1,213) =.922	0.338	N

As outlined in Table 5.36, education does not moderate the relationship between PU and behavioural intention.

Table 5.37 PU to Intent, moderated by Farm Size

Dependent Variable: Behavioural Intention	Predictors	Interaction Term	R2	ΔR^2	F	p	Significance
Main Effects Model	PU, Farm Size		0.317		F(2,214)= 51.105	0.000	Y
Interaction Effects Model		PU*Farm Size		0.034	ΔF (1,213) = 11.216	0.001	Y*

*indicates moderation is observed

Table 5.37 outlines that farm size acts as a moderator on the relationship between PU and behavioural intention.

5.7 Generalisation

The Expected Cross Validation Index (ECVI) for SEM Model 6 was examined to support claims of generalisability. As the value of 1.551 is lower than both the saturated (2.139) and independence model (11.765), outlined in Table 5.38, the value is deemed acceptable. Furthermore, the ECVI of SEM Model 6 (1.551) was compared to the same value for SEM Model 1 (1.657). As the value is lower, this reconfirms that SEM Model 6 best fits the data and is suitable to represent other similar populations.

Table 5.38 Expected Cross Validation Index – SEM Model 6

	ECVI	LO 90	HI 90	MECVI
Default model	1.551	1.394	1.745	1.612

	ECVI	LO 90	HI 90	MECVI
Saturated model	2.139	2.139	2.139	2.381
Independence model	11.765	11.036	12.527	11.787

5.8 Hypotheses Testing

The conceptual model with the hypothesised relationships, represented by causal paths between the latent constructs, is detailed in Figure 5.18 below. As outlined, Appendix O presents a summary of all the relevant parameter estimates including the regression estimates, standard error, critical ratio (CR), p value, and standardised regression estimates for the latent constructs in the model. Each hypothesis was tested against the CR value and the significance value of p. Hair *et al.* (2010) determine that for a path to be significant the CR should be >1.96 with a p-value of <.05.

A detailed analysis of each hypothesis result follows.

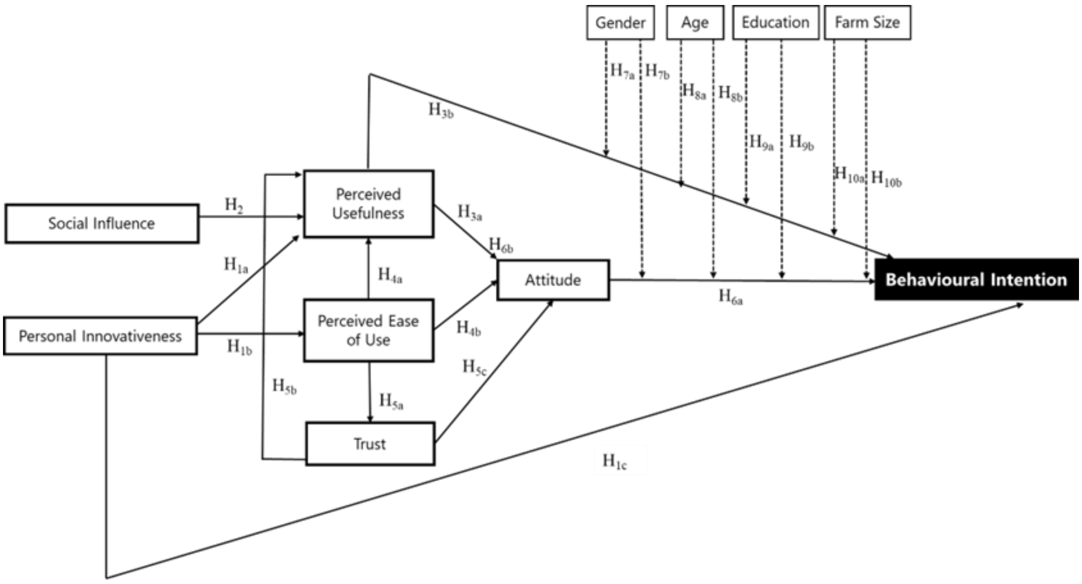

Figure 5.18 Hypothesised Model

The Influence of Personal Innovativeness on the Farmer's Perception of SFT and Intention to Adopt SFT.

H_{1a}: Personal innovativeness has a positive effect on the Perceived Usefulness of Smart Farming Technology.

H_{1b}: Personal innovativeness has a positive influence on the Perceived Ease of Use of Smart Farming Technology.

H_{1c}: Personal innovativeness has a positive direct effect on the Behavioural Intention to adopt Smart Farming Technology.

H_{1a}-H_{1c} relate to the influence that Personal Innovativeness in the IT domain (PIIT) has on the farmer's perception of the Perceived Usefulness (PU), the Perceived Ease of Use (PEOU) of SFT and the Behavioural Intention (BI) to adopt SFT.

Results for H_{1a} (β=0.268, CR>1.96, p<0.010) confirm that PIIT has an influence on the PU of SFT. Similarly, H_{1b} (β=0.722, CR>1.96, p<0.001) is supported, confirming that PIIT significantly influences the PEOU of SFT.

Furthermore, PIIT has a direct influence on the BI to adopt SFT (β=0.281, CR>1.96, p<0.010), supporting H_{1c}.

The Effect of Social Influence on the Perceived Usefulness of Smart Farming Technology

H_{2}: Social influence has a direct influence on the Perceived Usefulness of Smart Farming Technology.

H_2 relates to the effect that Social Influence has on the Perceived Usefulness of SFT. This hypothesis is supported (β=0.101, CR>1.96, p<0.05) confirming that SI influences PU.

The Impact of Perceived Usefulness on the Attitude towards Using SFT and the Behavioural Intention to Adopt SFT

H_{3a}: The Perceived Usefulness of SFT has a positive influence on the Attitude towards using Smart Farming Technology.

H_{3b}: The Perceived Usefulness of SFT has a positive direct effect on the Behavioural Intention to adopt Smart Farming Technology.

H_{3a} relates to the influence that PU has on the attitude towards using SFT. However, during the model refinement process, attitude was removed from the structural model to deliver a better model fit. As attitude was removed, H_{3a} could not be tested within the final model and therefore no results are presented.

H_{3b} hypothesises that PU has a direct influence on the Behavioural Intention to adopt SFT. Result show that this relationship was significant (β=0.454, CR>1.96, p<0.001) and thus the hypothesis is supported.

The Impact of Perceived Ease of Use On Perceived Usefulness and the Attitude towards using SFT

H_{4a}: The Perceived Ease of Use of SFT has a positive effect on the Perceived Usefulness of Smart Farming Technology.

H_{4b}: The Perceived Ease of Use of SFT has a positive effect on the Attitude towards using Smart Farming Technology.

H_{4a} purports that PEOU has a direct effect on the PU of SFT. This hypothesis was rejected (β=0.157, CR<1.96, p>0.05) suggesting that PEOU does not influence the PU of SFT.

H_{4b} relates to the influence that PEOU has on the attitude towards using SFT. However, as previously outlined, attitude was removed from the structural model during the model refinement process. As such, H_{4b} could not be tested within the final model and therefore no results are presented. Separately, a path was added from PEOU to BI during model fit testing, this was relationship was found to be insignificant (p>0.05).

The relationships between Trust, PEOU, PU and Attitude

H_{5a}: The Perceived Ease of Use of Smart Farming Technology has a direct influence on Trust in the SFT vendor.

H_{5b}: Trust in the SFT vendor has a positive influence on the Perceived Usefulness of Smart Farming Technology.

H_{5c}: Trust in the SFT vendor has a direct influence on the Attitude towards using Smart Farming Technology.

H_{5a} relates to PEOU influencing Trust. Results for H_{5a} (β=0.043, CR<1.96, p>0.05) reject this hypothesis, concluding that PEOU does not influence trust. The original hypothesis for H_{5b} related to trust influencing the PU of SFT. However, during the process of improving model fit, this relationship was changed to the PU of SFT influencing trust. As such, H_{5b}, as originally stated was not tested. Instead, the findings suggest an alternative relationship where PU directly influences trust. Results demonstrate that this relationship is significant (β=0.378, CR>1.96, p<0.001). Furthermore, H_{5c} was not tested due to attitude being removed from the model during the model fit process.

Attitude as a mediator between PU and Behavioural Intention, and having a direct influence on Behavioural Intention

H_{6a}: Attitude towards using SFT has a direct influence on the Behavioural Intention to adopt Smart Farming Technology.

H_{6b}: Attitude towards using SFT mediates the relationship between PU and the Behavioural Intention to adopt Smart Farming Technology.

The hypotheses for H_{6a} relates to attitude directly influencing BI. H_{6b} hypothesises that attitude acts as a mediator between the relationship between PU and BI. As outlined in Section 5.6.2, a mediation analysis was conducted to examine the mediating effect of these relationships. The total effect of the model was found to be significant (β =.3451, t=4.4689, p<.001). However, through testing alternative theories, attitude was removed from the model, resulting in a better model fit. As such, H_{6a} and H_{6b} are not tested.

The moderating effect of gender on the relationships between PU and Behavioural Intention and Attitude and Behavioural Intention

H_{7a}: The relationship between Perceived Usefulness and the Behavioural Intention to adopt SFT is moderated by Gender.

H_{7b}: The relationship between Attitude and the Behavioural Intention to adopt SFT is moderated by Gender.

H_{7a} and H_{7b} relate to the moderating effect that gender has on the relationship between PU and BI and the relationship between attitude and BI. Following analysis, the relationship between PU and BI was found to be statistically significant (β=0.454, CR>1.96, p<0.001). With regard to PU and gender, these variables accounted for a significant amount of variance in farmers' intentions to adopt SFT (R^2 =.334, F(1, 213)=53.606, p < .001). Moderation results, as outlined in Section 5.6.4, show that the effect that gender has on the relationship between PU and BI is insignificant (ΔR^2 = .000, ΔF(1,213)=0.001, p>.05). Therefore, H_{7a} is rejected, suggesting that the interaction between gender and PU is not a significant predictor of behavioural intention. In addition, as attitude was removed from the model, H_{7b} was not tested.

As gender was not a significant moderator, a t-test for independent samples was used in order to examine gender differences in the means of each of the factors in the model. The results of the means are shown in Figure 5.19. Women had lower mean scores for all factors. However, the differences were only statistically significant for PIIT ((t) = -2.832., p < .05), with females reporting lower levels of PIIT than men (F = 4.58 vs M = 5.10) and for BI ((t) = -2.096., p < .05), with males showing a higher behavioural intention to adopt SFT than females (F = 5.74 vs M = 6.07).

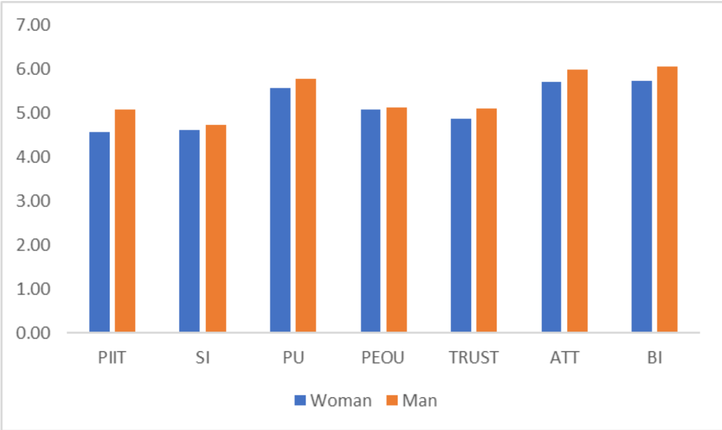

Figure 5.19 Gender Differences in Factor Means

The moderating effect of Age on the relationships between PU and Behavioural Intention and Attitude and Behavioural Intention

H_{8a} : The relationship between Perceived Usefulness and the Behavioural Intention to adopt SFT is moderated by Age.

H_{8b} : The relationship between Attitude and the Behavioural Intention to adopt SFT is moderated by Age.

H_{8a} and H_{8b} relate to the moderating effect that age has on the relationship between PU and behavioural intention and the relationship between attitude and behavioural intention accordingly. With regard to PU and age, these variables accounted for a significant amount of variance in farmers' behavioural intention to adopt SFT (R^2 =. 319, F(2, 214)= 51.619, p <.001). Furthermore, as outlined, the relationship between PU and behavioural intention is significant (β=0.454, CR>1.96, p<0.001). Results show that the age has a statistically significant moderating effect on the relationship between PU and BI (ΔR^2 = .018, ΔF(1,213)=5.7173, p<.05). Thus, H_{8a} is supported.

The interaction plot, as outlined in Figure 5.20, demonstrates that for both younger and older farmers, the higher the PU of SFT, the higher the BI to adopt SFT. For older farmers, an increase in the PU of SFT, leads to a more pronounced increase in BI, compared to younger farmers.

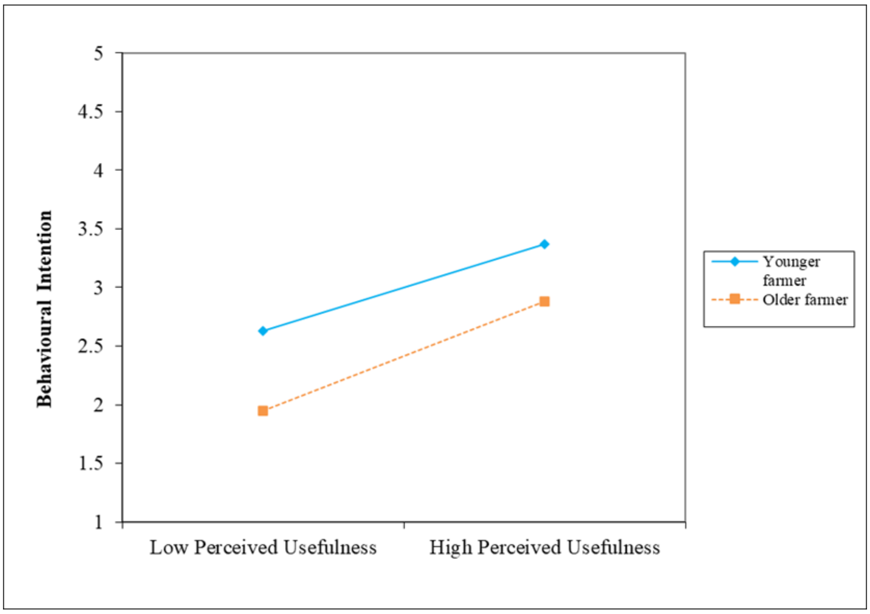

Figure 5.20 Relationship between PU and BI, moderated by Age

The interaction was further probed by testing the conditional effects of the moderator at three levels of age: 1 = 18-24, 2= 25-34, 4 = 45-54. At each level, the effect of PU on behavioural intention is significant ($p < .001$). As age increases, the effect of PU on BI also increases. Finally, as outlined previously, attitude was removed from the model, thus H_{8b} is not tested.

The moderating effect of Education on the relationships between PU and Behavioural Intention and Attitude and Behavioural Intention

H_{9a} : The relationship between Perceived Usefulness and the Behavioural Intention to adopt SFT is moderated by Education.

H_{9b}: The relationship between Attitude and the Behavioural Intention to adopt SFT is moderated by Education.

H_{9a} and H_{9b} relate to the moderating effect that education has on the relationship between PU and behavioural intention and the relationship between attitude and behavioural intention. First, the relationship between PU and intention was found to be statistically significant ($\beta=0.454$, $CR>1.96$, $p<0.001$). However, results show that education has no moderating effect on the relationship between PU and behavioural intention ($\Delta R2=.003$, $\Delta F(1,213)=.922$, $p>.05$). Thus, H_{9a} is rejected. As outlined previously, attitude was removed from the model, thus H_{9b} is not tested.

The moderating effect of Farm Size on the relationships between PU and Behavioural Intention and Attitude and Behavioural Intention

H_{10a} : The relationship between Perceived Usefulness and the Behavioural Intention to adopt SFT is moderated by Farm Size.

H_{10b} :The relationship between Attitude and the Behavioural Intention to adopt SFT is moderated by Farm Size.

H_{10a} and H_{10b} are related to the moderating effect that farm size has on the relationship between PU and BI and the relationship between attitude and BI. As previously discussed, the relationship between PU and BI was found to be statistically significant (β=0.454, CR>1.96, p<0.001). Furthermore, results show that farm size has a moderating effect on the relationship between PU and BI (ΔR2 =.304, ΔF(1,213)=11.216, p<.010). Thus, H_{10a} is supported. As illustrated in Figure 5.21, for both levels of farm size (low and high), as the PU of SFT increases, the BI to adopt SFT also increases. The interaction was further probed by testing the conditional effects of the moderator at three levels of farm size: 4 = (20-50ha), 5= 50-100ha, 6 = 100-500ha. At each level, the effect of PU on behavioural intention is significant (p < .001). However, as farm size increases from 20-50ha to 100-500ha, the strength of the effect decreases. This suggests that while PU still influences BI, for farmers with a larger farm size, the influence dampens as farm size grows.

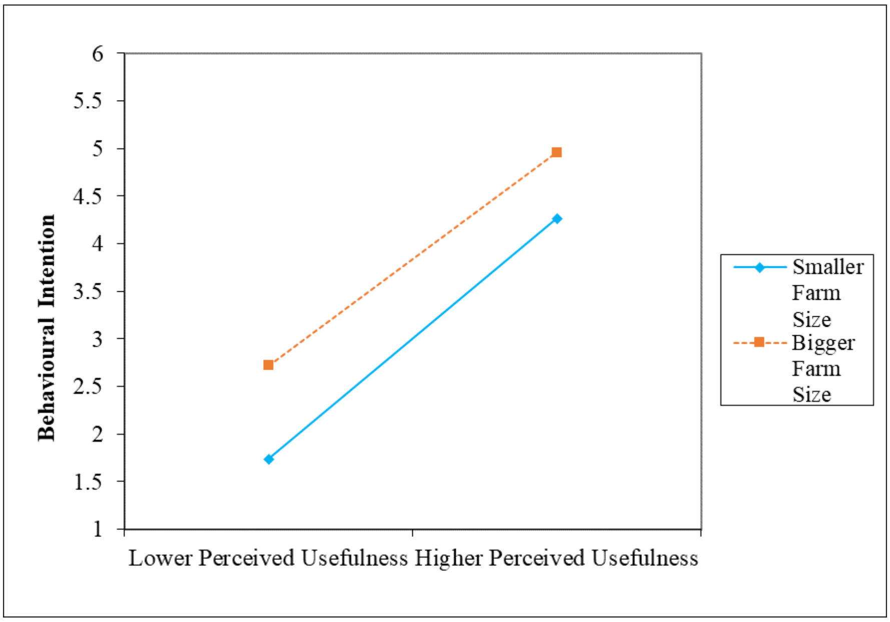

Figure 5.21 Relationship between PU and BI, moderated by Farm Size

H_{10b} was not tested as attitude was removed from the model. Table 5.39 summarises the full results from the hypotheses testing.

Table 5.39 Results from the hypotheses testing

Hypothesis	Hypothesis Statement	Estimate	P value	Result
H_{1a}	Personal innovativeness has a positive effect on the Perceived Usefulness of Smart Farming Technology.	0.268	0.004	Supported
H_{1b}	Personal innovativeness has a positive influence on the Perceived Ease of Use of Smart Farming Technology.	0.722	***	Supported
H_{1c}	Personal innovativeness has a positive direct effect on the Behavioural Intention to adopt Smart Farming Technology.	0.281	0.002	Supported
H_2	Social influence has a direct influence on the Perceived Usefulness of SFT.	0.101	0.028	Supported
H_{3a}	The Perceived Usefulness of SFT has a positive influence on the Attitude towards using SFT.	n/a	n/a	Not tested
H_{3b}	The Perceived Usefulness of SFT has a positive direct effect on the Behavioural Intention to adopt SFT.	0.454	***	Supported
H_{4a}	The Perceived Ease of Use of SFT has a positive effect on the Perceived Usefulness of SFT.	0.157	0.071	Rejected
H_{4b}	The Perceived Ease of Use of SFT has a positive effect on the Attitude towards using SFT.	n/a	n/a	Not tested
H_{5a}	The Perceived Ease of the Use of SFT has a direct influence on Trust in the SFT vendor.	0.043	0.518	Rejected
H_{5b}	Trust in the SFT vendor has a positive influence on the Perceived Usefulness of SFT*. (*however, PU positively related to Trust was tested and supported)	n/a	n/a	Not tested
H_{5c}	Trust in the SFT vendor has a direct influence on the Attitude towards using SFT.	n/a	n/a	Not tested
H_{6a}	Attitude towards using SFT has a direct influence on the Behavioural Intention to adopt Smart Farming Technology.	n/a	n/a	Not tested
H_{6b}	Attitude towards using SFT mediates the relationship between PU and the Behavioural Intention to adopt Smart Farming Technology.	n/a	n/a	Not tested

The moderation testing hypothesis and results are detailed in Table 5.40.

Table 5.40 Moderation Hypothesis Testing

Hypothesis	Hypothesis Statement	F	p	Result
H_{7a}	The relationship between Perceived Usefulness and Behavioural Intention is moderated by Gender.	ΔF (1,213) =0.01	0.973	Rejected
H_{7b}	The relationship between Attitude and Behavioural Intention is moderated by Gender.	n/a	n/a	Not tested
H_{8a}	The relationship between Perceived Usefulness and Behavioural Intention is moderated by Age.	ΔF(1,213) =5.717	0.018	Supported
H_{8b}	The relationship between Attitude and Behavioural Intention is moderated by Age.	n/a	n/a	Not tested
H_{9a}	The relationship between Perceived Usefulness and Behavioural Intention is moderated by Education.	ΔF(1,213) =.922	0.338	Rejected
H_{9b}	The relationship between Attitude and Behavioural Intention is moderated by Education.	n/a	n/a	Not tested
H_{10a}	The relationship between Perceived Usefulness and Behavioural Intention is moderated by Farm Size.	ΔF (1,213) = 11.216	0.001	Supported
H_{10b}	The relationship between Attitude and Behavioural Intention is moderated by Farm Size.	n/a	n/a	Not tested

The Squared Multiple Correlations (SMC) or R^2 equivalents for each endogenous variable in the model were finally assessed. This indicates the variance level reflected by the predictors in the model (Byrne, 2010). Table 5.41 presents the SMC or R^2 equivalents for each endogenous variable.

Table 5.41 Table of Squared Multiple Correlations

Variable	SMC Value	Interpretation
PU	0.312	31.2% of the variance in PU is explained by its predictors PIIT and SI.
Trust	0.170	17.0% of the variance in Trust is explained by PU.
PEOU	0.508	50.8% of the variance in PEOU is explained PIIT.
Intention	0.670	67.0% of the variance in Behavioural Intention is explained by PIIT and PU.

5.8.1 Control variables

SFT experience was the only control variable used in this study. It was found to have a controlling effect on behavioural intention ($\beta=0.076$, $CR>1.06$, $p<0.05$). Furthermore, the hypothesised relationships remain valid while accounting for the control variable.

5.9 Conclusion

This chapter outlined the robust, statistical examination procedures of the data that were followed to allow testing and validation of the conceptual model and associated hypothesised relationships, as outlined in Chapter 3. Pre-SEM analysis tests to determine sphericity, normality and communality of data were firstly conducted. Next, internal consistency and composite reliability were confirmed for all constructs. Convergent, discriminant and nomological validity were determined for the multi-item scales used in the research, ensuring that the indicators were correlated, sufficiently different and consistent with theoretical expectations. The measurement model and modification indices were then assessed to deliver an optimal model fit. Following this process, nested model, mediation and alternative model testing was performed and analysed. This resulted in attitude being dropped from the model to deliver a more parsimonious and better fit model. The effect of the control variable (SFT experience) and moderating variables (age, gender, education and farm size) were then also tested. The final step was testing the hypotheses which were supported, with the exception of H_{4a}, H_{5a}, H_{7a} and H_{9a}. As attitude was dropped from the model, testing of the hypotheses related to this construct were not conducted. The final comprehensive model, as outlined in Figure 5.22, with non-significant paths removed, demonstrated a good fit. The following chapter discusses the key findings from this study in relation to the existing theories and body of knowledge.

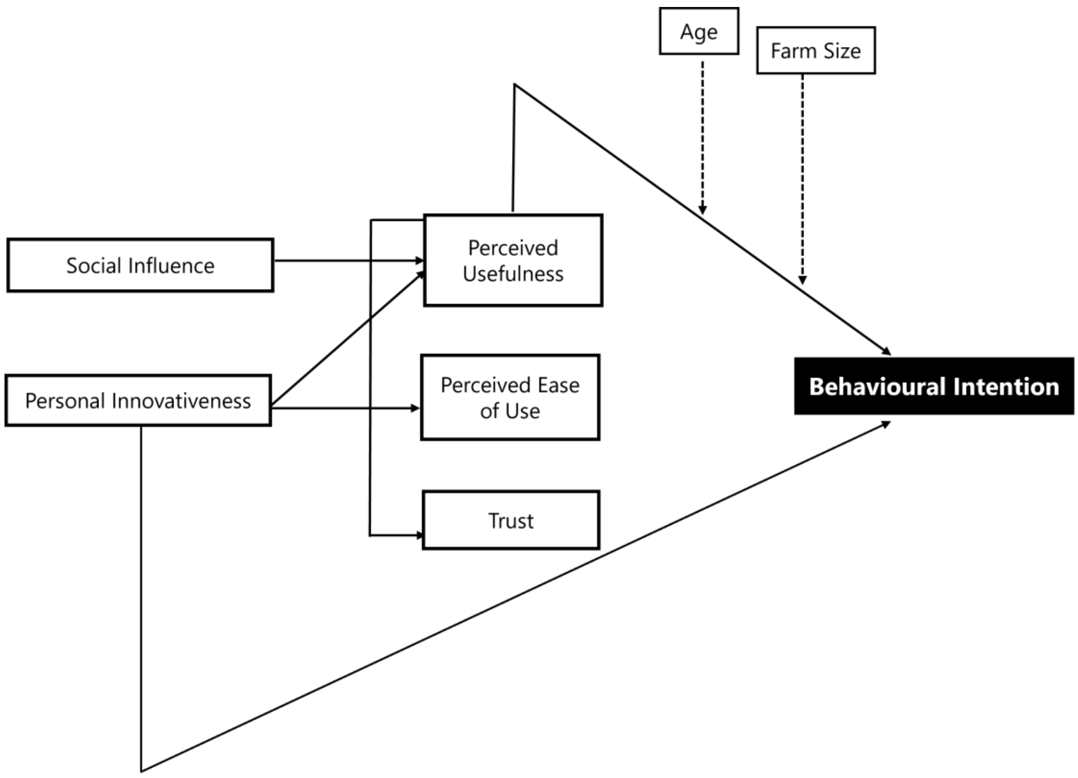

Figure 5.22 Final Verified Model

Chapter 6: Discussion

6.1 Introduction

Considering the potential of Smart Farming Technology (SFT) to improve agricultural sustainability, the overarching objective of this study was to determine the influence of key factors on farmers' behavioural intentions to adopt SFT, thereby advancing substantive theory. This was done through the development of a conceptual model and hypotheses, examining factors which influence behavioural intention such as personal innovativeness (PIIT), social influence (SI), the farmer's perception of usefulness and ease of use of SFT, trust in the SFT vendor and the farmer's attitude towards using SFT. These hypotheses were validated through rigorous statistical examination with the majority being supported, as elaborated in greater detail in this chapter. This study provides insights through extending the lens of the Technology Acceptance Model (TAM), in particular, focusing on novel contributions in areas such as personal innovativeness and trust. This chapter discusses the key findings which are presented in brief initially, and then expanded upon in subsequent sections. These findings are aligned and contrasted with literature from the technology adoption domain.

This study firstly moves beyond the application of TAM and other behavioural theories to the context of agriculture and SFT adoption, and develops a contemporary, integrated model which addresses the deficiencies of existing models. This new model acknowledges that the intention to adopt SFT is not solely based on perceived ease of use (PEOU) and perceived usefulness (PU) of the technology, as proposed by the original TAM (Davis, 1986). In particular, social influence, trust in the vendor and personal innovativeness as a personality trait have been successfully integrated with TAM, and hypotheses testing demonstrates significant relationships with these variables and the constructs within TAM. This represents a significant advancement in understanding the multi-faceted nature of the farmer's behavioural intention to adopt SFT. This improved understanding can lead to more effective strategies to encourage the adoption of SFT, tailored to address the specific needs of farmers. From a theoretical perspective, incorporating these additional constructs presents a more robust TAM with improved predictive power and relevance. It addresses the criticisms of TAM for largely neglecting additional variables such as social influence and personality traits (Bagozzi, 2007a; Chen *et al.*, 2002; Lee *et al.*, 2003; Rosen, 2004). This study therefore builds on the literature that recognises that understanding farmers' perceptions as well as their overall interest in technology is critical to predicting behaviour (Caffaro *et al.*, 2019; de Lauwere *et al.*, 2020; Giua *et al.*, 2022). Furthermore, this research supports Osrof *et al.* (2023) in determining that solely focusing on the economic or cost-benefit perspective of SFT adoption is not sufficient due to the complex and multi-dimensional nature of the process.

Findings from this study demonstrate that the behavioural intention to adopt SFT is directly influenced by the perceived usefulness and the personal innovativeness of the farmer. The relationship between PU and BI was considerable, whereas the relationship with perceived ease of use on BI was non-significant. This supports seminal studies from Schultz and Slevin (1975), Robey (1979) and Davis (1989) who determine that users are primarily driven to adopt technology based on its functional benefits. It also supports more recent findings from an agricultural context on the importance of usefulness as a construct on farmers' intentions to adopt SFT (Thomas *et al.*, 2023). Therefore, demonstrating the benefits of SFT in terms of improved efficiency, improved yield and facilitating easier working conditions, such as reduced labour, is critical to increasing intention to adopt SFT. Furthermore, the moderating role of age and farm size on the relationship between perceived usefulness and intention is established in this research. This reinforces findings from Rossi Borges *et al.* (2019) and Das *et al.* (2019) who determine that larger-scale farmers are more likely to adopt SFT than their smaller-scale counterparts. Equally, age being a moderator on the relationship between PU and intention supports several empirical studies (Morris *et al.*, 2005; Rübcke von Veltheim *et al.*, 2021; Venkatesh and Davis, 2000; Venkatesh *et al.*, 2003).

Next, the results demonstrate that personal innovativeness as a personality trait has a strong influence on the farmer's perceptions of SFT and the behavioural intention to adopt SFT. This purports that individual differences play a substantial role in the intention to adopt technology. Consequently, this supports the work of Agarwal and Prasad (1999) and Rogers (2003) in understanding that individuals differ in their intention to adopt technology due to their level of innovativeness. This highlights the need for tailored communication strategies from SFT vendors and policymakers, adapted to the various personal innovativeness level of farmers. It further emphasises the need for continuous education and training for farmers to support the development of personal innovativeness as a trait, as emphasised by Walder *et al.* (2019).

Rogers (2003) underscored the importance of understanding the influence of peers and influential actors on the adoption rate of new innovations. Thus, the inclusion of social influence in this research. Incorporating the construct directly addresses the gap as outlined by Shang *et al.* (2021) who determine that the influence of the farmer's network on technology adoption decisions has not been sufficiently examined in empirical studies. It explicitly tackles the criticism from Burton (2004) who deduces that many studies which adopt a behavioural approach to understand intention fail to account for social influence. Furthermore, the call for more research on the impact of social influence is addressed (Eckhardt *et al.*, 2010; Graf-Vlachy *et al.*, 2018; Legris *et al.*, 2003; Vannoy and Palvia, 2010; Venkatesh *et al.*, 2003). The overall findings demonstrate that social influence impacts the perceived usefulness of SFT. In particular, the important role of peer farmers in shaping the farmer's perceptions regarding the usefulness of SFT was deduced. This supports Naspetti *et al.* (2017) who found that social influence had an impact on the perceived usefulness of sustainable production strategies for dairy farmers. With usefulness highly correlated with behavioural intention, it is crucial that positive, albeit unbiased, perceptions are shared in the farmer's network to further encourage the intention to adopt SFT.

Finally, this research adds to the body of literature determining the role that trust in the technology provider plays on the intention to adopt SFT. Trust was conceptualised from a social-psychological perspective as interpersonal trust, relating to the farmer's cognitive beliefs regarding the competency, benevolence and integrity of the SFT vendor, as detailed by Mayer *et al.* (1995). The inclusion of trust in the study was relevant as it has been highlighted as important in B2B relationships (Kemp *et al.*, 2018) and equally for the successful adoption, implementation, and long-term use of SFT (Jakku *et al.*, 2019; Walter *et al.*, 2017). The results suggest that the PU of the technology influences trust in the SFT vendor. Thus, if the farmer perceives the technology as useful in terms of increased job efficiency and increased productivity, then their perception of the integrity and competency of the vendor increases. This contradicts seminal studies from Gefen *et al.* (2003) and Pavlou (2003) who posit that trust is a predictor of perceived usefulness. This contradiction suggests that the relationship between PU and trust is multifaceted and could vary according to the context, the technology in question, and the user population. It also suggests differences in results, depending on how the construct was operationalised. Furthermore, the perception of ease of use had a non-significant relationship with trust, indicating that although this construct is important, its role is not pivotal in developing trust in the SFT vendor. The following sections discuss these key findings in more detail, starting with the influence on behavioural intention which the model seeks to explain. The influence of the antecedents on BI are then discussed in order of importance.

6.2 Influences on the Behavioural Intention to adopt SFT

The outcome variable in this research was the behavioural intention (BI) to adopt SFT. Previous literature determines that there is a strong, positive relationship between intention and actual behaviour (Ajzen, 1991; Ajzen *et al.*, 2009; Fishman *et al.*, 2020; Herath, 2013; Sheeran, 2002; Tao, 2009; Venkatesh *et al.*, 2003). Indeed, in TAM, Davis (1986) explains that BI is a better predictor of actual behaviour than attitude. Soto *et al.* (2019) indicate that awareness of precision agriculture technology is high, while Kernecker *et al.* (2019) explain that farmers have high expectations of what SFT can deliver. Thus, it is not surprising that the overall intention to adopt SFT in this study was strong, with only 3% of farmers indicating that they have no intention to adopt SFT. Furthermore, the propensity to adopt SFT was robust, with nearly half of the sample indicating an intention to adopt in the next year. This is important as Osrof *et al.* (2023) explain that awareness and knowledge of SFT are key drivers of intention and adoption. Findings from this study thus support the literature which suggests that farmers recognise how SFT can help them farm more efficiently and productively in the future (Giua *et al.*, 2022; Kernecker *et al.*, 2019; Knierim *et al.*, 2019; Marescotti *et al.*, 2021; Walter *et al.*, 2017).

Results outline that the category of SFT most likely to be considered by farmers was farm management information systems (FMIS), followed by Precision Agriculture (PA) systems and then autonomously operating machines. This order is understandable considering the higher level of expertise and financial investment associated with PA systems and autonomous machines. Kernecker *et al.* (2019) explain that FMIS are widely adopted across farms, regardless of sector and farm size, which could further explain the category having the highest intention to adopt among farmers in this study. Interestingly, Balafoutis *et al.* (2020) also determine that funding from EU projects has been predominately directed towards FMIS development, which could also have an impact on awareness and adoption intention. Furthermore, the market for FMIS is relatively mature with multiple vendors offering various FMIS solutions, tailored to different farming needs

(Fountas *et al.*, 2018), thus indicating more widespread availability for farmers. Although considered the less sophisticated form of SFT, Köksal and Tekinerdogan (2018) outline how FMIS deliver advantages for the farmer in terms of decision-making and planning, while Saiz-Rubio and Rovira-Más (2020) highlight increased management efficiency as a key benefit.

Overall, 67.0% of the variance in behavioural intention, as outlined in Section 5.8, is explained, indicating that PU and PIIT as predictors are effective in explaining its variance. Perceived usefulness of SFT had a direct, positive influence on the intention to adopt, supporting one of the key relationships from TAM (Davis *et al.*, 1989). Thus, the findings determine that perceived usefulness is a critical determinant of BI, supporting several authors who stipulate that the construct is one of the most influential beliefs on technology adoption and acceptance (Sun and Zhang, 2006; Taylor and Todd, 1995; Yousafzai *et al.*, 2007a). This research reinforces this finding as the second strongest relationship in the model was between perceived usefulness and BI. As outlined in Section 5.8, the strongest relationship in the model was between PIIT and PEOU, which is discussed in Section 6.3. Additionally, the research aligns with Kernecker *et al.* (2019) who found that farmers strongly agree that SFT are useful for farming and that they surpass previous tools in effectiveness. It further supports Paudel *et al.* (2021) who determine that farmers' intention to adopt SFT is largely driven by the perceived usefulness of SFT.

PU having a strong relationship with BI supports Caffaro *et al.* (2020), while Flett *et al.* (2004) also conclude that PU is a major determinant of BI to adopt dairy production technologies. Similarly, previous research from Michels *et al.* (2020b) and Toma *et al.* (2016) also find support for this strong relationship between PU and BI. Thus, if the farmer believes that SFT will improve their productivity and job performance and help them conduct on-farm tasks, they will have a higher intention to adopt. This underscores the benefit of adding an organisational behaviour or B2B perspective, given that the farmers in this study are predominantly influenced by the efficacy of SFT in facilitating their on-farm operations.

From further analysis regarding the barriers that prevent farmers from adopting SFT, as discussed in Section 5.2.3, farmers cited cost as the biggest barrier followed by no clear return on investment as the second most impeding factor. This is in line with Kernecker *et al.* (2019) who determine that due to the wide range of SFT available, it is difficult for farmers to fully understand what benefits these technologies have to offer. Similarly, Osrof *et al.* (2023) outline that to facilitate SFT adoption, farmers must have a positive perception of the trade-off between costs and benefits. This suggests that there is a need for technology providers, knowledge transfer agents, policymakers and farm advisors to diffuse information about the usefulness of SFT in a clearer manner. Communication materials such as case studies, video testimonials and frequently asked questions content, which clearly highlight the practicality of SFT in terms of economic benefit, social sustainability and environmental gains, are important. This can foster the perception of usefulness, thus helping to develop a positive intention to adopt. Detailed cost-benefit analysis showing the return on investment can help to further improve the perceived usefulness of SFT and, accordingly, influence behavioural intention. Finally, implementing pilot initiatives or on-farm demonstrations to showcase the full capabilities of SFT would be a welcomed initiative to further diffuse the advantages of SFT adoption.

Results, as outlined in Section 5.8, demonstrate that personal innovativeness (PIIT) has a significant positive effect on behavioural intention. This suggests that farmers with a higher level of PIIT also have a higher behavioural intention to adopt SFT. The research supports Osrof *et al.* (2023) who conclude that a farmer being open-minded and curious towards new technologies is important for SFT adoption. Equally, farmer innovativeness is outlined as a driver for technology adoption with such farmers being more open to trying new farming practices (Gemtou *et al.*, 2024). Venkatesh (2021) further outlines the importance of examining personal traits in technology adoption studies. The result of PIIT directly influencing BI was a considerable finding, as prior works suggest that there is no direct relationship between PIIT and intention (Beza *et al.*, 2018; Lu *et al.*, 2005; Mohr and Kühl, 2021; Molina-Maturano *et al.*, 2021). However, the study from Beza *et al.* (2018) examined the relationship between PIIT and Ethiopian farmers' intentions to adopt mobile Short Message Service (SMS). The authors themselves noted that SMS may not be seen as an innovative technology, which could potentially have influenced the results. Equally, Molina-Maturano *et al.* (2021) examined intention to adopt agricultural smartphone applications and found PIIT had no influence, which again it could be argued may be associated with the relative ease of use and widespread adoption of the technology in question. Mohr and Kühl (2021) suggest that the small sample size (n=84) for their study of German farmers' acceptance of artificial intelligence, may have influenced their findings. Perhaps more notable is that Lu *et al.* (2005) found no relationship between PIIT and intention, attributing this to the non-work-related nature of the technology (Wi-Fi) being studied. Thus, as farmers' intentions to adopt SFT relate to improved work performance, this may have resulted in a positive relationship between PIIT and BI in this study. Results do, however, support Emmann *et al.* (2013) who investigated the effect of personal innovativeness on farmers' acceptance of biogas innovation and found it to be significant. However, their operationalisation of personal innovativeness was different to the PIIT construct and they examined acceptance rather than adoption. Similarly, Aubert *et al.* (2012) determined that personal innovativeness impacts the adoption of precision agriculture. Their operationalisation was taken from the Taylor and Todd (1995) self-efficacy measure which focuses on feeling comfortable using technology, the individual's ability to use the technology on their own, and their ability to use technology without help. This is similar to PIIT, as outlined in Section 2.8.5.2, but PIIT is more focused on experimenting with new technologies. Ciftci *et al.* (2021) conclude that inconsistent findings with regard to the effect of PIIT on behavioural intention may be related to the population of interest, while Mao *et al.* (2014) suggest that the technological development of the area in question may also impact results. Thus, as SFT adoption was under examination and as farmers generally perceived themselves as having a high level of PIIT, this may have influenced the result of PIIT influencing BI. However, it is evident that in order to foster a positive intention to adopt SFT, encouraging farmers to experiment and try new technologies is critical. This can be done through supportive training programmes which focus on driving the farmer's inner motivation to experiment with the various categories of SFT.

Results indicate that PEOU did not have a significant effect on BI. This was not hypothesised in the original conceptual model in this study, but when attitude was removed during model testing, a direct path was drawn from PEOU to BI, consistent with the original TAM. However, the relationship was found to be insignificant. This is an interesting observation as Kernecker *et al.* (2019) and Das *et al.* (2019) deduce that farmers perceive SFT as overly complex. The findings, however, support Wachenheim *et al.* (2021) who determine that the PEOU of unmanned aerial vehicles for pesticide application in farms in China does not influence adoption intent. Furthermore when Caffaro *et al.* (2020) were assessing the influence of PU and PEOU on farmers' intentions to adopt technological innovations, they dropped PEOU from their model due to the path not reaching significance, and its inclusion resulting in an unacceptable model fit. They deduce that a statistically insignificant relationship between PEOU and BI may be due to other external factors such as the availability of technology impacting the intention, even if the farmer feels they have the necessary skills to adopt technology. Finally, Li *et al.* (2021) outline that although PEOU is an influential variable, it does not increase the willingness of farmers to adopt photovoltaic agriculture.

Adams *et al.* (1992) used TAM to determine the relationships between perceived usefulness, perceived ease of use and system usage in two separate studies involving different technologies. They assessed email and voicemail in Study 1 and spreadsheets and graphics in Study 2. Inconsistent findings were found in terms of the importance of the perceived ease of use construct, which they conclude may vary according to experience and sophistication of the system. Similarly, in a separate study replicating TAM, Subramanian (1994) also found no support for PEOU influencing predicted system usage. They deduce that this may be due to prior experience and actual inherent ease of use of the technology. Interestingly, the original TAM finds support for PEOU not influencing actual usage but having an impact on intention, thus determining that the variable is more important in the early stages of the user learning about the technology, as detailed by Yousafzai *et al.* (2007a). The statistically insignificant relationship in this research may, therefore, be due to the majority of farmers in this study using some form of FMIS, which are arguably the more straightforward category of SFT to operate. In addition, McCaig *et al.* (2023) outline that using SFT requires a certain skillset. As a large proportion of farmers were already using FMIS, this may indicate that they believe they already possess the necessary skillset, making the perceived ease of using new systems less of a factor in their future intentions to adopt other SFT. Furthermore, the farmers in this study were relatively well-educated, with over 50% receiving either a bachelor’s degree, masters or PhD. Thus, it could be argued that they already have a level of education to allow them to use SFT effectively and thus PEOU is not an influencing factor.

6.2.1 The impact of moderating and control variables on BI

Various studies suggest that a farmer’s behavioural intention to adopt SFT is influenced by socio-demographic variables such as age, gender, and level of education. For example, as outlined in Sections 2.8.5.4 – 2.8.5.6, younger farmers are more likely to adopt technology (Cavallo *et al.*, 2015), female farmers have less access to technology and therefore have lower adoption rates (Ragasa *et al.*, 2014) and higher education levels increase the farmer's likelihood of adopting technology (Aubert *et al.*, 2012). Furthermore, the larger the size of the farm, the more likely the farmer is to adopt SFT (Rossi Borges *et al.*, 2019). Moderation tests were conducted, as outlined in Section 5.6.4, on the relationship between PU and behavioural intention and also the relationship between attitude and behavioural intention. Overall, the relationship between PU and behavioural intention is moderated by age and farm size. The moderating role of gender and education was insignificant. Additionally, as discussed in Section 5.6.3.2, attitude was dropped from the final model, so moderation tests relating to the relationship between attitude and BI are not discussed.

This research concludes that farmers with larger size farms have a higher baseline intention to adopt SFT, even with lower perceptions of usefulness. Several studies related to technology adoption in agriculture find a similar relationship, determining that farmers with larger land parcels are more likely to adopt technology, compared to those with a smaller land mass (Blasch *et al.*, 2022; Caffaro and Cavallo, 2019; Das *et al.*, 2019; Rossi Borges *et al.*, 2019; Schukat and Heise, 2021a). This is due to increased investment capability from larger-scale farmers (Tamirat *et al.*, 2017) alongside SFT often being designed to favour the larger farm (Fleming *et al.*, 2018). This swayed adoption of SFT by larger-sized farms can, however, further heighten the digital divide discussed by Fleming *et al.* (2018). Indeed, Bronson (2019) emphasises the necessity of making SFT accessible to all farm sizes and types. This research suggests that due to small-sized farmers' intentions being lower, cost implications and applicability of SFT to smaller land parcels may be an issue.

Furthermore, farm size moderates the relationship between PU and BI. Intrinsically, small-scale farmers' intentions to adopt SFT increase more substantially with their perception of the technology's usefulness. As such, the influence of perceived usefulness on behavioural intention is stronger for smaller-scale farmers than for bigger-scale farmers. Mizik (2022) explain that due to the perceived high cost to adopt SFT, small-scale farmers need to be very clear on the benefits of implementation before they invest. Furthermore, the finding could be attributed to the fact that certain SFT may already be implemented on larger farms and additional SFT may require significant modification to the existing way of working, thereby limiting its PU. For example, Kernecker *et al.* (2019) explain that interoperability and connectivity between SFT devices can be an issue for farmers with more than one SFT. Overall, the finding highlights the need for SFT vendors and policymakers to deliver initiatives that target smaller-scale farmers with subsidies and training to encourage broader adoption of SFT. Equally, SFT vendors need to consider the possibility of introducing scalable solutions that could be more suitable and relevant to small scale farmers. Co-design initiatives could help deliver more cost-effective and suitable innovations for the smaller scale farmer (Michels *et al.*, 2020a). This is critical in ensuring smaller farmers' future are safeguarded (Mehrabi *et al.*, 2020).

In addition, for both younger and older farmers, the higher the PU of SFT, the higher the BI to adopt. Younger farmers have a higher baseline intention to adopt SFT, regardless of their perceptions of its usefulness. This supports several studies assessing the relationship between the farmer's age and intention to adopt technology on-farm (Isgin *et al.*, 2008; Mohr and Kühl, 2021; Pierpaoli *et al.*, 2013; Tey and Brindal, 2012). Venkatesh *et al.* (2003) found that age acts as a moderator on the relationship between performance expectancy, likened to PU, and behavioural intention. The authors found the effect of the moderator to be more pronounced for younger people. However, in this study, for older farmers, an increase in the PU of SFT leads to a more pronounced increase in BI, when compared to younger farmers. Previous studies, in other contexts, suggest that older individuals may need more convincing regarding the advantages of new technologies due to their higher levels of technological anxiety and lower levels of experience with digital tools (Zhou *et al.*, 2024). The finding thus supports Molina-Maturano *et al.* (2021) who find that the effect of performance expectancy on intention is more important for older farmers. This suggests that older farmers may be particularly motivated by the clear utility benefits related to SFT implementation. Consequently, targeted marketing strategies considering the varying needs and perceptions of farmers across different age groups are needed.

Gender did not moderate the relationship between PU and behavioural intention in this study. This suggests that regardless of gender, PU influences the BI of SFT similarly. This directly contradicts studies from several authors who support the relationship (Chang *et al.*, 2019; Gefen and Straub, 2000; Morris *et al.*, 2005; Nahar, 2022; Terblanche and Kidd, 2022; Venkatesh and Davis, 2000). It supports Wong *et al.* (2012) who found that gender had no moderating influence on the TAM relationships, in their study of students' acceptance of computer technology. It further supports Schukat and Heise (2021b) who determine that gender was not a significant moderator in their study of German farmers' intentions to adopt SFT. Conversely, while gender does not moderate the relationship between PU and intention, it does play a role in other aspects of technology adoption. Results from the independent samples t-test, as discussed in Section 5.8, showed significant differences in the mean scores for PIIT and BI, with men scoring higher than women. It should be noted, however, that the sample size for females was relatively small in this study (approximately 21%). López-Bonilla and López-Bonilla (2012) found that men self-reported higher levels of PIIT than women when examining general information technology behaviour. Similarly, Venkatesh *et al.* (2000) found that men are more likely to adopt technologies earlier than women, which they attributed to differences in innovativeness levels. The result in this study may therefore be due to situational factors including cultural, social, economic, or personal reasons that affect men and women differently. For example, Ragasa *et al*., (2014) state that female farmers have a lower adoption rate of technologies than men due to societal land transfer practices and lower access to services. Women are also seen as generally more risk-averse than men which impacts their technology adoption decisions (Bendell *et al.*, 2020). Furthermore, the difference between genders in their perceptions of personal innovativeness highlights the need to ensure that female farmers are exposed to, and have the opportunity to experiment with, new technologies. It also raises the importance of SFT having a user-friendly design that caters to both men and women and differing levels of PIIT (McCaig *et al.*, 2023).

The inclusion of education as a moderating variable on the relationship between PU and BI directly addresses the criticism of Li *et al.* (2014) who determine that the moderating role of education has largely been ignored by several behavioural models. Although, 31.9% of the variance in BI can be explained by education and PU combined, education level did not have a moderating effect on the relationship between PU and BI to adopt SFT in this study. This suggests that regardless of education level, the benefits associated with SFT are universally acknowledged by farmers. As highlighted previously, the awareness and expectations of what SFT can deliver are generally high, thus, it is concurred that the intrinsic benefits of SFT are learnt independently of education levels. Finally, experience in using SFT was used as a control variable in this research. By controlling for SFT experience, the study aimed to isolate the impact of other independent variables on the intention to adopt SFT, ensuring that the observed effects are not due to variations in previous SFT use among farmers. The results were found to be significant, suggesting that level of experience influences behavioural intention to adopt SFT.

6.3 The importance of Personal Innovativeness (PIIT) as a construct

As previously outlined in Section 5.8, PIIT had a significant direct effect on behavioural intention. Furthermore, results demonstrate that PIIT acts as an antecedent to both the PU (Perceived Usefulness) and PEOU (Perceived Ease of Use) variables from TAM. 50.8% of the variance in PEOU is explained by PIIT, as outlined in Section 5.8. While 31.2% of the variance in PU is explained by its predictors, PIIT and SI, indicating other factors may also be influential. Overall, the findings suggest that individuals with higher levels of personal innovativeness perceive SFT as both easier to use and more useful. It should be noted, however, that Knierim *et al.* (2018) determine that how easy the farmer perceives a SFT as being to use is potentially related to their ease of access to SFT as well as their innovativeness. Regardless, the results critically demonstrate the importance of fostering IT innovativeness among farmers to enhance their perception of the ease of use of SFT, in particular. These findings support the seminal study from Agarwal and Prasad (1998) who explain that individuals that demonstrate high levels of PIIT positively recognise the PEOU and PU of new IT. This also confirms results from Mohr and Kühl (2021) who deduce that the farmer's personal innovativeness increases both the PU and PEOU of artificial intelligence in farming. Interestingly, Flett *et al.* (2004) found that being innovative and using new technologies was not a key objective for farmers in their study of dairy farmers' technology adoption decisions. Providing a satisfying lifestyle was most important. As such, given that PIIT influences PEOU and PU, promoting the development of PIIT as a way to achieve a better output on farm and work-life balance may be an appropriate marketing strategy.

Results support Lewis *et al.* (2003), albeit in a different context, who found that the personal innovativeness of public university employees had a significant effect on the PU and PEOU of IT. They found that the relationship between PIIT and PU was stronger than PIIT and PEOU. Findings also support Lu *et al.* (2005) who determine that PIIT influences the PU and PEOU of wireless internet services. However, they found the relationship between PIIT and PEOU to be stronger than PIIT and PU, as did Zarmpou *et al.* (2012) in the context of mobile applications. The discrepancy in the relative importance of the relationships between PIIT and PU and PIIT and PEOU implies that it may be context and technology dependent. For example, in the case of the study on university employees from Lewis *et al*. (2003), the level of education and comfort with technology may be a further influencing factor. In the study from Lu *et al*. (2005), MBA students were the population of interest, and the wireless technology was relatively new. In this doctoral study, the relationship between PIIT and PEOU was more significant than PIIT and PU. Significantly, it represented the strongest relationship in the model. Again, this may be due to the relatively high level of education achieved by farmers in this sample. Overall, it suggests that farmers that are more innovative have stronger perceptions of how easy SFT is to use, rather than its usefulness. However, emphasising the intuitive aspect of SFT may be more suitable to target early innovators.

Venkatesh (2000) assessed the determinants of PEOU and found that self-efficacy, which has been likened to the PIIT construct as discussed, is influential. He explains that if an individual has not used a technology, then their overall level of comfort in using technology will impact their assessment on whether other technology is easy to use. Sun *et al.* (2010) also found support for innovativeness being an important determinant of PEOU. Importantly, Venkatesh and Davis (1996) determine that self-efficacy continues to be an important determinant of PEOU, regardless of the level of experience the user has with the technology. Thus, examining the relationship between self-efficacy and PIIT would be a relevant topic for future research.

When examining alternative theories for model fit, it was hypothesised that PIIT acts as a moderator between perceptions and BI, as discussed in Section 5.6.4. Model fit testing and moderation results from the research demonstrated that this relationship was insignificant. This suggests that whether the farmer perceives themselves as innovative or not, their intention to adopt SFT when they perceive it as useful remains consistent. PIIT as an antecedent supports findings from Yi *et al.* (2006a) who determine that the construct is an antecedent rather than a moderator. It also supports findings from previous research that the role of PIIT as a moderator is insignificant (Agarwal and Prasad, 1998; Alkawsi *et al.*, 2021; Okumus *et al.*, 2018). Therefore, personal innovativeness directly influences how the farmer perceives SFT, rather than affecting the strength or direction of the relationship between perceived usefulness and behavioural intention. This makes an important theoretical contribution to the extant literature by clarifying the importance of including PIIT as an antecedent in studies of technology adoption. In addition, including PIIT as a factor in this study narrows the gap highlighted by several authors related to the exclusion of personality variables in technology adoption studies (Ciftci *et al.*, 2021; Dabholkar and Bagozzi, 2002; Rosen, 2004). Integrating PIIT as a personality trait with TAM also answers the call from many researchers in an agriculture context focusing on technology adoption (Ali *et al.*, 2017; Bukchin and Kerret, 2018; Rose *et al.*, 2018a).

Overall, the findings demonstrate the critical importance of the PIIT construct and the need to develop the personal innovativeness of farmers and in particular female farmers to facilitate SFT adoption. Participation in agri-networks could help to further foster innovativeness. Tepic *et al.* (2012) note however that frequency of contact in such networks is central to developing innovativeness. Workshops and seminars as well as pilot testing of the technology on a smaller scale before full implementation, as outlined previously, can be useful activities to cultivate this personality trait. Walder *et al.* (2019) explains that farmers that are seen as conservative and that value security, exhibit lower levels of PIIT, thus delivering training in an environment that minimises the risk for the participant is important. This may be done in smaller groups, through personalised support, or through incremental learning initiatives. In addition, identifying farmers that perceive themselves as innovative in the domain of IT can potentially help overall adoption levels of SFT. This can be done by encouraging these innovators to provide tangible benefits of SFT to other farmers, demonstrating the practical benefits of adoption in usefulness terms such as increased yield and more efficient use of resources. Finally, Lu *et al.* (2005) suggest that personal traits have a key impact on adoption intentions, perhaps more than instrumental beliefs such as the perceived usefulness and perceived ease of use of a technology. This is supported by this research with the importance of PIIT being delineated and consequently should be a key target for policymakers.

6.4 The role of Social influence (SI)

Venkatesh *et al.* (2003) define social influence as the individual's perception of the social pressure or influence to adopt a particular behaviour or technology. Results from this study confirm that SI influences the farmer's perception of the perceived usefulness of SFT. This empirically supports Naspetti *et al.* (2017) who determine that the opinion of relevant people to the farmer influences their behaviour. Equally, Giua *et al.* (2022) find that people the farmer trusts, colleagues and other farmers influence their perceptions of SFT. This implies that if people who influence the farmer's behaviour, or those who are important to the farmer, believe in the utility of SFT then the farmer is more likely to perceive SFT as useful. This is an important finding in terms of disseminating the benefits of SFT implementation using influential actors within the farmer's network to increase adoption intention. The finding is in line with numerous studies both in an agricultural context (Castiblanco Jimenez *et al.*, 2020; Dai and Cheng, 2022; Naspetti *et al.*, 2017), and in other technological contexts determining the effect of SI on PU (Horst *et al.*, 2007; Iskandar and Yusep Rosmansyah, 2018; Lin *et al.*, 2003). It also supports Schepers and Wetzels (2007) meta-analysis of TAM, investigating the role of social influence on PU, where they find that there is a significant relationship between both variables. Moreover, it strengthens the argument from Venkatesh and Davis (2000) regarding the importance of including the construct in behavioural models. It further determines that the farmer's perception of the usefulness of SFT is not solely determined by the intrinsic features of the technology but also, importantly, by others in their network.

From a B2B perspective, it further supports findings from Rampersad *et al*. (2012) that details the importance of networks in a technology adoption context. Klerkx *et al*. (2010) highlight that farmers' participation in such networks can facilitate positive innovative behaviour. Thus, the endorsement from significant others or influential figures in the farmer's network can act as a validation of the perceived usefulness of SFT. Consequently, the influence of actors in the farmer's network was separately examined to determine their impact on the farmer's perception of usefulness. As outlined in Section 4.4.3.1, the social influence construct comprises identification and compliance measures. With regard to identification ("*<Network actor> that I know would think that I should use Smart Farming Technology"*), other farmers were most influential, followed by family members, farm advisors and farmers' associations. In terms of compliance ("*Generally speaking, I want to do what <network actor> I know would think that I should do"*), other farmers were by far the most influential, followed by farm family members, farmers' associations, and farm advisors. This contradicts Barnes *et al.* (2019b) who suggests that the role that peer farmers play in SFT adoption may be limited due to the associated costs of purchase and implementation, and the potentially challenging nature of the technology. It does, however, support previous theoretical and empirical work highlighting the importance that farmers place on other farmers' opinions (Blasch *et al.*, 2022; Knierim *et al.*, 2018). Thus, this deduces the relative importance of peer farmers in disseminating knowledge among their network related to the usefulness of SFT. Indeed, Giua *et al.* (2022) explain that peer farmers play a fundamental role in improving expectations of what SFT can deliver. Social media can be an effective tool to broaden the farmer's network and information flow, negating the potentially homophilous nature of the offline network, as discussed by Dilleen *et al.* (2023). Furthermore, Caffaro *et al.* (2020) explain that personal sources of information, such as family and neighbours, are most effective at encouraging potential adoption of technological innovations for Italian farmers. Thus, the family collective alongside the farmer’s network has a significant influence on the farmer’s decision-making process regarding technology adoption, supporting the extant literature (Huber *et al.*, 2018; Schneider *et al.*, 2012).

Furthermore, farmers mostly disagreed with the statement that farm advisors are knowledgeable about SFT. Although Eastwood *et al.* (2017b) highlight the importance of farm advisors and extension agents in transferring knowledge to farmers, results from this study suggest that the farm advisor role is limited due to the complex nature of SFT. Indeed, Ayre *et al.* (2019) note that SFT represents a challenge for advisors and farmers alike due to the combination of integrating novel digital and physical elements. Charatsari *et al.* (2022) states that advisors often view SFT as a disruption and therefore need to build their digital competencies to facilitate increased SFT adoption. The findings further support the work of Higgins and Bryant (2020) who deduce that there are two schools of thought regarding advisory services. Some farmers believe that advisors play a sense-checking role and help with implementation of SFT while others consider that advisors have a very narrow role in SFT adoption. Moreover, Giua *et al.* (2022) note that farmers perceive external support from experts such as advisors and professional associations as inadequate. In this study, farmers’ associations were seen as more informed, although farmers still mostly disagreed with the overall statement that they were knowledgeable. Consequently, findings suggest that advisors and associations need to improve their knowledge and understanding of SFT, the associated benefits and how to implement and integrate on-farm. This could be done through specialised training with SFT vendors, but also through collaborations with academic institutions and funded research projects. Additionally, dissemination of knowledge to farmers regarding SFT, particularly related to its PU, is needed through sharing case studies, best practice guides and farmer testimonials.

6.5 Trust matters

The integration of trust with the TAM is noteworthy, as stipulated by Belanche *et al.* (2012), confirming the importance of trust in business relationships (Doney and Cannon, 1997; Kemp *et al.*, 2018; Morgan and Hunt, 1994). Osrof *et al.* (2023) and McCaig *et al.* (2023) highlight that the farmer’s perception of trust in SFT and SFT vendors influences their adoption decisions. Issues relating to security, capability and data reliability affected these perceptions. Trust in this study is represented from a social-psychological perspective, representing the integrity and competency of the SFT vendor and not trust in the specific technology. Findings support Jayashankar *et al.* (2018) who determine that trust is an antecedent to the adoption of new technology. Subsequently, the results outline that perceived usefulness has a direct effect on the trust towards the SFT vendor. The relationship between PU and trust was the third most significant in the model. This demonstrates that the farmer's perception of the usefulness of SFT, impacts the level of trust they have in the SFT vendor. Thus, if the farmer perceives SFT as useful, they are more likely to trust the vendor. This is a key finding and demonstrates that information highlighting the significant benefits of SFT, in terms of return on investment, improved productivity and labour savings, can make the farmer more likely to trust the SFT vendor. However, it should be noted that only 17.0% of the variance in trust is explained by PU, suggesting that other factors influence the variable.

The original hypothesised relationship stated that trust influenced PU, as suggested by literature (Gefen *et al.*, 2003; Pavlou and Gefen, 2004). However, this path was altered during the alternative theory testing, as outlined in Section 5.6.3, and subsequently the relationship was confirmed. In their meta-analysis of the integration of trust and TAM, Wu *et al.* (2011) determine that such testing of the relationships between TAM variables and trust is common. First, this result challenges Duang-Ek-Anong *et al.* (2019) who argue, in their study of the adoption of Internet of Things in smart farming in Thailand, that trust is not important. Next, the finding contradicts several established studies (Belanche *et al.*, 2012; Dhagarra *et al.*, 2020; Gefen *et al.*, 2003, Tung *et al.*, 2008; Wu and Chen, 2005; Zhang *et al.*, 2021). The alternative relationship of PU impacting trust does, however, have empirical support from Amin *et al.* (2014) for mobile websites, Roca *et al.* (2009) in online trading systems and Li and Yeh (2010) for mobile commerce. Furthermore, Benamati *et al.* (2010) find support for PU influencing trust in the context of e-commerce environments. Suh and Han (2002) determine that PU has a direct effect on consumers' trust in Internet banking. Similarly, Zhang *et al.* (2020) deduce that PU influences consumers' trust in autonomous vehicles. Finally, Mou and Cohen (2014) established that the PU of e-services influences the trust in e-service providers. Consequently, SFT vendors need to clearly communicate the usefulness of SFT to help build trust. However, they need to be cognisant not to over-emphasise the benefits of SFT, as Jerhamre *et al.* (2022) deduce that over-promising can drive farmer scepticism regarding usefulness.

Perceived usefulness influencing trust rather than reversely may be influenced by the context, the operationalisation of trust, the population and the technology in question. For example, Zhang *et al.* (2021) determine that initial trust is built upon cognitive beliefs relating to the PU of the technology. However, in the seminal study from Gefen *et al.* (2003) the research is based on experienced, repeat online customers where it is argued ongoing trust is captured. Indeed, the authors acknowledge that they omit elements of trust which are more relevant to initial trust formation. Furthermore, in this study, trust is operationalised using second order factors comprising nine items, measuring benevolence, integrity and competency. Benevolence was subsequently dropped during model fit testing, as detailed in Section 5.3.2. The measure of trust from Gefen *et al.* (2003) for their study, which solely focused on trust, was captured using twenty items. Furthermore, interpersonal trust was measured in this study. However, Gefen *et al.* (2003) measured both institutional trust and calculative trust, which would have impacted results. Belanche *et al.* (2012) and Dhagarra *et al.* (2020) failed to clearly state what perspective they were defining trust from, and used three items to operationalise it. Thus, these differences in operationalisation may have influenced the results. Future research examining institutional-based trust in an SFT context would be interesting to conduct and compare with the findings from this study. Critically, this research supports McEvily and Tortoriello (2011) and Schoorman *et al.* (2015) who criticise much of the literature examining trust for not being explicit enough in terms of measurement and operationalisation of the construct.

As discussed in Section 4.4.2, trust in this study was conceptualised as comprising competency, integrity, and benevolence items. Comparing the mean score of each of these first order factors showed that competency scored highest, followed by integrity and lastly benevolence. If SFT vendors can improve farmers' perceptions of their competency and integrity, this could lead to increased trust. As highlighted in Section 2.8.5.3, being transparent with the use of data from SFT (Jakku *et al.*, 2019), demonstrating flexibility regarding implementation of SFT on larger and smaller farms (van der Burg *et al.*, 2019) and giving guarantees related to interoperability between technologies (Jukan *et al.*, 2016) could lead to increased trust levels. Having clear data-sharing principles could also help improve the farmer's perception of integrity, as detailed by van der Burg *et al.* (2019).

The relationship between PEOU and trust was not significant. This was an unexpected finding as this relationship has received significant support in the literature (Belanche *et al.*, 2012; Gefen *et al.*, 2003; Pavlou, 2003; Zhang *et al.*, 2021). The finding was however consistent with Chen and Barnes (2007) who found that PEOU does not impact trust in online vendors. Equally, Zhang *et al.* (2020) determine that PEOU does not influence trust of autonomous vehicles. Results suggest that farmers are prioritising the vendors' competency and integrity over the ease of use of SFT. Furthermore, farmers may be trusting of a SFT vendor, regardless of the ease of use of their technology. Again, as highlighted previously, differences in conceptualisation and operationalisation of trust could explain the findings. Thus, for SFT vendors, this highlights the importance of marketing strategies focused on the usefulness of the technology, showcasing their relationships with farmers and building a strong reputation.

6.6 The mediating influence of Perceived Ease of Use and Perceived Usefulness

Results demonstrate the PU partially mediates the relationship between PIIT and behavioural intention, as discussed in Section 5.6.2. This implies that the farmer's innovativeness level influences their perception of the usefulness of SFT, which in turn impacts their intention to adopt SFT. This is important for SFT vendors and policymakers when designing communication materials. Consequently, a key focus should be on the PU of SFT to help encourage further adoption. As outlined in Section 6.2, PIIT also has a direct effect on BI. This implies that although PU is important, personal innovativeness has its own direct relationship on the farmer's intention to adopt SFT. This underscores the importance of both the inherent innovativeness level of farmers and the perceived attributes of the technology in influencing the farmer's intention to adopt SFT. This contradicts Jackson *et al.* (2013) who determine that the only influence PIIT has on BI is through PU. The context was however different to agriculture and focused on intention to adopt an e-commerce purchasing system in hospitals.

Overall, results demonstrate that perceived ease of use has a positive but statistically insignificant relationship with perceived usefulness. This, therefore, suggests that the farmer's perception of the ease of use of SFT is not related to their perception of usefulness. The result could be attributed to the sample of farmers surveyed in this study self-reporting high levels of PIIT and were also relatively well-educated. However, the finding directly contradicts the original TAM developed by Davis (1989) and several other empirical studies advocating for the relationship between PEOU and PU (Jones *et al.*, 2002; King and He, 2006; Mathieson, 1991; Taylor and Todd, 1995; Venkatesh and Davis, 2000; Yousafzai *et al.*, 2007a). In an agricultural context, it also disagrees with Flett *et al.* (2004) who found that there is a positive correlation between PEOU and PU for the adoption of technology in dairy farming in New Zealand. Studies from other agricultural contexts from Negi and Nasreen (2021), Mohr and Kühl (2021) and Castiblanco Jimenez *et al.* (2021) also deduce there is a significant relationship between PEOU and PU. However, the findings support Canavari *et al.* (2021) who determine that the perceived ease of use of variable rate irrigation technology does not influence its perceived usefulness. Equally, Adrian *et al.* (2005) examined the influence of the PEOU of precision agriculture technologies (PAT) on PU and found it did not have an effect on adoption. While, Aubert *et al.* (2012) also find no support for PEOU influencing PU for PAT. As both these studies relate specifically to PAT, further research is needed to determine if this finding can be replicated in other SFT contexts. Additionally, Sheppard and Vibert (2019) suggest that PEOU could moderate the relationship between an antecedent variable and PU, rather than having a direct effect. This suggests that PEOU might not increase PU directly but could change how other factors lead to PU. Thus, the moderating role of PEOU as a variable warrants further examination in other contexts.

Overall, the PEOU of SFT does not influence either the behavioural intention to adopt SFT or its perceived usefulness. This suggests that in the context of the model in this research, the role of PEOU is more nuanced, rather than having a direct effect on intention. It is, however, influenced by the intrinsic characteristics of the farmer, in this instance, their personal innovativeness. Although PEOU was not an influential variable, it is noted that when asked to rate the factors that would encourage them to adopt SFT, as discussed in Section 5.2.3, farmers rated technologies that are more straightforward to use as the most influential factor. This still highlights the importance of a user-centred design for SFT. Vendors could therefore work with farmers in the design process to improve the usability of technology and thus help to encourage a more positive intention towards adoption, as cited in the literature (Kenny and Regan, 2021).

6.7 Conclusion

This chapter discussed the main findings emerging from this study examining the key factors which influence farmers' behavioural intentions to adopt SFT. The development of a novel model, successfully integrating TAM with additional variables, represents a substantial enhancement in understanding the multifaceted nature of the factors influencing farmers' behavioural intentions to adopt SFT. Interesting insights relating to the effect of PIIT, social influence and Trust in the SFT vendor have been uncovered, delivering both academic and managerial contributions. The study builds on the literature which recognises that understanding farmers' perceptions as well as their overall interest in technology is critical to predicting behaviour. Furthermore, using an organisational behaviour or B2B lens delivers a more integrated approach to understanding the influences of farmers' BI to adopt SFT, combining individual, interpersonal and organisational factors such as farm size and trust in B2B relationships.

Overall, the behavioural intention to adopt SFT is directly influenced by the perceived usefulness of the technology. PU is therefore a critical influencer on intent, thus SFT vendors need to prioritise communicating the practical benefits of SFT implementation. Personal innovativeness of the farmer was highlighted as directly influencing BI as well as the PU and PEOU of the technology. Thus, more work is needed to cultivate PIIT as a personality trait through training, education and peer networking. Social influence impacts the perceived usefulness of SFT, highlighting the importance of the farmer's network and, in particular, peer farmers in sharing knowledge and information regarding SFT. Furthermore, trust in the SFT vendor influences the PU of the technology, highlighting the importance of building initial trust through demonstrating the SFT vendors' competency and integrity. However, PEOU of SFT was not a critical influencing factor in this study, purporting that farmers are willing to consider an element of complexity if the technology delivers benefits.

The next chapter outlines the main theoretical and practical contributions of the research, followed by the implications of the findings. The limitations of the research are discussed, and future research agendas are thereby outlined, building on the findings from this research.

Chapter 7: Conclusion

7.1 Introduction

This final chapter provides a review of the overarching research objective in this study, which is to examine the key influences on farmers' intentions to adopt Smart Farming Technology (SFT). Chapter 1 outlined the research background, gave an overview of Smart Farming Technology (SFT) and introduced the overall research question and research domains. Chapter 2 delivered a comprehensive literature review, using the Technology Acceptance Model (TAM) as a guiding framework for the research, while accounting for the context of a B2B setting. The need to contemporise TAM, incorporating additional variables, with a focus on SFT adoption intention, was evident. Chapter 3 presented a conceptual model and a series of associated hypotheses for examination. In Chapter 4, a discussion related to the research design and methodology was presented, encompassing the researcher's deductive and positivistic approach. Chapter 5 outlined the analysis undertaken, using structural equation modelling (SEM). In Chapter 6, the main findings from the research were discussed. Finally, in this chapter, a summary of the research process and findings are presented, followed by the main theoretical contributions of the study. Next, the practical implications arising from the key findings are discussed. The subsequent section focuses on the limitations of the research. To conclude, potential avenues for future research are outlined.

7.2 Summary of the Research Process

The agriculture sector is facing many well-documented challenges, as outlined in Chapter 2. These challenges include increased agricultural intensification to feed a growing population, the need to be more environmentally aware and sustainable, the need to attract a younger population to the sector and the need to protect the farmer's income, ensuring that farming as a career choice is economically viable. As discussed in Section 2.2, SFT can potentially help to overcome some of these challenges, delivering economic, environmental and social sustainability. This can be achieved through the technologies providing data or resources to the farmer to allow them to optimise their on-farm operations. As a result, savings can be achieved in terms of both time and money, yield can be increased and improved, and autonomation of certain jobs can free up the farmer's time. The adoption rate of SFT is, however, lower than expected as, leading to the explicit need for more research to determine the key factors influencing the farmer's behavioural intention to adopt SFT and their associated impact. Much of the existing research has focused on cost-benefit models, largely ignoring key variables such as perceptions, personal traits and social influence. Furthermore, a large proportion of the extant research tends to focus on individual technologies rather than the category of SFT, which limits the generalisation of the findings. In addition, farmers are increasingly identifying as business owners, moving away from the traditional or conventional producer identity, thus driving the need for a B2B or Organisational Buying Behaviour (OBB) perspective for this study. These highlighted gaps guided the overarching objective of this study: to advance substantive theory through an examination of the key factors influencing farmers' behavioural intentions to adopt SFT.

To address the research objective, a comprehensive literature review was conducted. This initially examined OBB to factor in the context of a B2B environment. Although OBB relates to buying behaviour, the literature domain also discusses how organisations assess the potential utility and compatibility of goods and services, which are critical determinants of adoption intention. Subsequently, the Technology Acceptance Model (TAM) was used as the theoretical foundation for the study, focusing on the importance of attitudes and perceptions towards SFT. A review of the literature highlighted the critical importance of incorporating additional variables namely personal innovativeness, social influence and trust in the SFT vendor with TAM. The incorporation of these variables was important to enable a thorough examination of both the antecedents and moderators impacting the intention to adopt SFT.

Several hypotheses were presented in Chapter 3, stemming from the extensive review of the literature. A contemporary, integrated model was developed and presented for examination. Various research approaches were considered but a quantitative approach was taken, based on the researcher's philosophical stance of positivism, alongside the call for more empirical studies examining technology adoption in the agricultural sector. Consequently, a web-based survey was selected as the research instrument. This survey was shared on social media and through networks such as farmers' associations and interest groups. SEM was used as the statistical technique to analyse the complex relationships between the constructs presented in the conceptual model. Hierarchical moderated linear regression was also conducted to test the moderation hypotheses. Rigorous model fit testing was undertaken, as outlined in Section 5.5, to determine the appropriateness and adequacy of the conceptual model in representing the underlying data. Hypotheses testing was then conducted to examine the proposed relationships within the model and to determine their significance. Accordingly, the results indicate that several of the hypotheses were supported, and model fit analysis suggested a high probability that the model accurately represents the target population.

7.3 Summary of Research Findings

Overall, the findings demonstrate that the intention to adopt SFT is directly influenced by the perceived usefulness (PU) of SFT and the personal innovativeness in the IT domain (PIIT) of the farmer. However, the relationship between perceived ease of use (PEOU) and behavioural intention (BI) was statistically insignificant. In particular, PU had the strongest influence on the intention to adopt SFT, thus highlighting its critical importance. This demonstrates that farmers are interested in potentially adopting technology that will improve their activities on farm in terms of increased efficiency, increased productivity and improved job performance. This supports seminal research from key authors (Davis, 1989; Schultz and Slevin, 1975; Venkatesh *et al.*, 2003) who highlight that the impact of the technology on the user's job performance has a strong relationship with the intention to adopt. Furthermore, as PEOU had no direct relationship with intention to adopt SFT, it can be suggested that farmers are willing to put up with a degree of difficulty if the technology will deliver benefits. The findings suggest that the influence of the PEOU construct may vary according to experience or sophistication of the technology in question, as outlined previously by Adams *et al.* (1992) and Subramanian (1994). Conversely, the insignificant relationship between PEOU and BI supports the studies conducted by Caffaro *et al.* (2020) and Adrian *et al.* (2005). These researchers established that, in a farming context, there is no discernible relationship between the intention to adopt SFT or precision agriculture technologies and PEOU.

PIIT also had a direct impact on the intention to adopt SFT. Personal innovativeness, in this context, refers to the willingness of individuals to embrace new technologies, taken from Agarwal and Prasad (1998). Farmers who consider themselves as innovative are more inclined to consider adopting SFT. This finding is significant as it underscores the role of individual characteristics in SFT adoption. Those scoring high on PIIT are more likely to be risk takers (Agarwal and Prasad, 1998) and demonstrate high levels of self-confidence (Abubakre *et al.*, 2020; Jackson *et al.*, 2013), which can further impact BI. The significant relationship between PIIT and BI contradicts previous research that failed to establish a relationship between the constructs (Beza *et al.*, 2018; Lu *et al.*, 2005; Mohr and Kühl, 2021; Molina-Maturano *et al.*, 2021). Again, this discourse from previous studies may be related to the population of interest and the sophistication of the technology, as underlined by Mao *et al.* (2014) and Ciftci *et al.* (2021) who suggest that the technological development of the area in question may impact results.

Furthermore, the study identified a substantial relationship between PIIT and both PU and PEOU. This concludes that farmers who deem themselves as innovative in the domain of IT tend to perceive SFT as both easier to use and more useful for their farm. This correlation highlights that PIIT not only influences the intention to adopt SFT but also shapes perceptions about the technology itself. This aligns with several studies that find similar support for these relationships, both in the context of SFT adoption and in the wider context of IT adoption (Agarwal and Prasad, 1998; Lewis *et al.*, 2003; Lu *et al*., 2005; Mohr and Kühl, 2021; Zarmpou *et al*., 2012). In this research, the relationship between PIIT and PEOU was the strongest relationship in the model, indicating that personal innovativeness is a major predictor of how easy a person perceives the technology to be. This may be due to farmers who are open to technology being more confident in their ability to learn and use new SFT, thus perceiving it as easy to use. However, as outlined, perceiving SFT as easy to use does not have a direct influence on the overall behavioural intention to adopt it.

Social influence, which is defined as the degree to which the farmer perceives that others important to him/her believe that they should use SFT, impacted the PU of SFT. This infers that if important others perceive SFT as useful, the farmer is also influenced by this perception. This is consistent with several authors who find support for this relationship in an agriculture setting (Castiblanco Jimenez *et al.*, 2020; Dai and Cheng, 2022; Naspetti *et al.*, 2017). This finding is important as it determines that the PU of SFT is not just influenced by characteristics of the technology but is also shaped by significant others in the farmer's network. This thereby highlights the importance of the network in the adoption of technology. Further analysis of the actors who influence the farmer's perceptions of SFT highlight that peer farmers are most influential. This supports previous research on SFT adoption who determine the importance of peer farmers in disseminating knowledge related to SFT (Blasch *et al.*, 2022; Knierim *et al.*, 2018). The role of farm advisors and farming associations was not as clear, as farmers indicated in this study that they did not find these actors knowledgeable on SFT. This was consistent with other studies that deduce that farm advisors play a limited role in SFT adoption due to a lack of digital competencies and knowledge (Ayre *et al.*, 2019; Charatsari *et al*., 2022, Giua *et al.*, 2022; Higgins and Bryant, 2020).

One of the novel insights from this study is the relationship between PU and trust in the SFT vendor. Trust is a multidimensional construct encompassing perceptions of the SFT vendor's competency and integrity. The study found that as farmers perceive SFT as useful, their trust in the technology vendor increases. Thus, trust is pivotal in the farming sector where long-term relationships and reliability are highly valued. For SFT vendors, demonstrating the usefulness of their technology is critical to building stronger trust with farmers who may adopt SFT. As outlined in Section 6.5, the relationship does have empirical support, but however contradicts previous studies (Belanche *et al.*, 2012; Dhagarra *et al*., 2020; Gefen *et al*., 2003; Tung *et al.*, 2008; Wu and Chen, 2005; Zhang *et al.*, 2021). This discrepancy may be due to differences in the operationalisation of trust, as discussed in 4.4.3, in addition to whether initial trust or continued trust was under examination. For example, this study used an operationalisation of trusting beliefs from McKnight *et al.* (2002) focusing on second-order factors and initial trust. However, the study from Gefen *et al.* (2003), who determined that trust influences PU, examined continued trust.

Both farm size and age were found to be significant moderators on the relationship between PU and BI. Farmers with a larger landmass have a higher baseline intention to adopt SFT, even with lower PU levels, which is consistent with previous studies (Blasch *et al.*, 2022; Caffaro and Cavallo, 2019; Das *et al.*, 2019; Rossi Borges *et al.*, 2019). The research suggests that the influence of PU on the behavioural intention to adopt SFT is more pronounced for farmers with smaller land parcels compared to those with larger land parcels. This suggests that the adoption of SFT may require more extreme changes for small-scale farmers, thus the influence of PU in their decision-making. With regard to age, younger farmers show a higher baseline intention to adopt SFT, regardless of their perception of its usefulness. Age having an influence on farmers' technology adoption decisions supports previous research in the agriculture domain (Aubert *et al.*, 2012; Cavallo *et al*., 2015; Groher *et al.*, 2020; Higgins and Bryant, 2020; Isgin *et al.*, 2008; Tey and Brindal, 2012). However, for older farmers, an increase in the perceived usefulness of SFT leads to a more noticeable increase in their intention to adopt. This therefore suggests that older farmers need to perceive clear, tangible benefits from SFT to consider its adoption. Finally, SFT experience as a control variable was significant, demonstrating the farmer's experience with SFT can influence their perceptions regarding the technology and their intention to use it.

7.4 Theoretical Contributions

A number of significant contributions are provided to knowledge, following this research. The major contribution is the development of a novel and integrated model which empirically verifies the key influences on the farmer's behavioural intention to adopt SFT. This model brings together the key constructs of the Technology Acceptance Model with additional variables including social influence, personal innovativeness and trust in the SFT vendor to determine how these factors influence the intention to adopt SFT. Thus, this research represents a substantial and pertinent addition to existing knowledge, particularly considering the critical role of SFT adoption, given its potential in terms of economic, social and environmental sustainability, as highlighted by previous research (Adnan *et al.*, 2019; Bacco *et al.*, 2019; Brewster *et al.*, 2017; Javaid *et al.*, 2022; Kernecker *et al.*, 2019; Mahmud *et al.*, 2020; Medvedev and Molodyakov, 2019; Moysiadis *et al.*, 2021; Pivoto *et al.*, 2019; Regan, 2019). Further theoretical contributions are discussed in more detail below.

7.4.1 Advancing the Technology Acceptance Model

A considerable theoretical contribution of the research is its role in advancing TAM in different contexts. The model validates the use of TAM in explaining farmers' intentions to adopt SFT. More importantly, modifications to the original model by including additional antecedent variables (personal innovativeness, social influence and trust in the SFT vendor) and moderating variables (farm size and age) increases its explanatory and predictive power. This was done by testing the original model and the model with the new variables incorporated, as discussed in Section 5.6.1. This new, integrated model outlines the complex dynamics in the relationships between variables and highlights the importance of considering multiple factors in understanding farmers' intentions to adopt SFT. The extension to TAM demonstrates the importance of including individual traits (age, personal innovativeness), organisational factors (farm size, trust) as well as social influence when determining intentions to adopt technology. Conversely, this highlights that technology adoption is not solely related to the perceptions of the technology but that including social constructs and personal traits can further increase its explanatory power. Furthermore, by incorporating these variables, this research addresses several criticisms of TAM and other decision-making theories for largely ignoring these constructs (Bagozzi, 2007a; Benbasat and Barki, 2007; Lee *et al*., 2003; Mathieson, 1991; Sun and Zhang, 2006; Wu and Lederer, 2009) and for being overly simple (Bagozzi, 2007a; Shachak *et al.*, 2019). Consequently, the research addresses the deficiencies of existing behavioural models, as highlighted in Chapter 2 and 3.

Furthermore, integrating trust in the technology vendor and its associated dimensions of integrity and competency with TAM, delivers a further theoretical contribution. It firstly broadens the model's applicability and relevance, as previously discussed. In this study, model testing determined that PU influencing trust delivered a better model fit, challenging several studies as outlined in Section 7.3. This suggests that the relationship between these variables may be more complex than previously thought, and further examination of established theoretical paths to uncover insights is required. This also raises the possibility of the relationship between these variables being bidirectional.

Removing attitude from the model also delivers several theoretical contributions. In the original TAM, attitude towards using technology played a role as a mediator between PU and PEOU, and the behavioural intention to adopt the technology. Analysis of this original TAM demonstrates that attitude has a partial mediating effect on BI (Davis, 1986). However, its exclusion from TAM would lead to a more parsimonious model (Yousafzai *et al*., 2007a). Several researchers, however, called for more research to incorporate attitude with TAM to determine its effects (Brown *et al.*, 2002; Kim *et al.*, 2009; López-Bonilla and López-Bonilla, 2017; Teo, 2009; Ursavaş, 2012; Yang and Yoo, 2003). Attitude was originally included in this study but during the model fit testing was subsequently dropped to deliver a better model fit and more parsimonious model, as discussed in Section 5.6.3.2. Consequently, results from this research challenge Wu *et al.* (2011) and López-Bonilla and López-Bonilla (2017) who explain the importance of including attitude in behavioural models. The research, therefore, contributes to the ongoing discussion of the role of attitude in technology adoption models and the importance of parsimony in model testing and design. Findings are consistent with Davis *et al.* (1989) who determine that attitude does not facilitate the causal relationships between perceptions of the technology and intention to use the technology. Furthermore, it could be suggested that attitude towards using the technology is captured in the PU and PEOU variables (Malatji *et al.*, 2020).

7.4.2 Generalisability of the Model

A further considerable contribution of this integrated model is the application of TAM to farmers, farming, and the SFT adoption context. The research therefore broadens the applicability of TAM to other businesses, workplaces and user populations. This is consistent with previous theories, in particular the seminal work from Ryan and Gross (1943) regarding diffusion among farmers, which resulted in the Diffusion of Innovation theory from Rogers (1962). Furthermore, the study focused on the category of SFT rather than one specific technology to increase its generalisability. By focusing on the category of smart technology within the farming context, the development of an integrated model allows for a comparative analysis across different sectors that use smart technology, for example SMEs and microenterprises. Likewise, responses were received across a range of farming contexts, as discussed in Section 5.2.1, which improves the generalisability of the model. Furthermore, as discussed in Section 5.7, the value of the Expected Cross Validation Index (ECVI) is low, suggesting that if the study was replicated with a different sample from the same population, the results would likely be similar. This is crucial for the reliability and validity of the model's implications in broader contexts.

7.4.3 Distinct need for TAM to be updated

The third theoretical contribution relates to recognising the distinct need for the construct items in TAM to be updated. This is particularly important given the advent of artificial intelligence across many industries and sectors. In this study, perceived usefulness influenced the behavioural intention to adopt SFT, but perceived ease of use was not an instrumental construct on the perception of usefulness or intention. However, TAM was developed by Davis (1986) at a time when technologies in the workplace were relatively new and primarily basic computer systems. Davis (1986) explained that the primary goal of TAM was to develop a model that was capable of explaining adoption across a broad range of user populations and end-user computing technologies. While TAM is a well-established model and has received considerable empirical support, it is argued that the model needs to be updated in the era of smart technology. Indeed, previous criticism of TAM centres around its applicability for electronic platforms (Persico *et al.*, 2014) while Benbasat and Barki (2007) argue that understanding what makes a system useful requires further examination. PU in the context of smart technology can offer features such as predictive analytics and automation, considerably more sophisticated than the original technologies studied in TAM, which should be considered. This is relevant for the adoption of smart technology in the workforce. Similarly, PEOU in a smart technology context, might reflect the need to integrate smart technology with existing technologies already deployed. TAM items therefore need to be updated to reflect the sophistication and complexity of modern technologies.

Integrating social influence with TAM is also a significant contribution, demonstrating the importance of peer farmers, in particular, in disseminating knowledge on SFT. The original TAM primarily focused on the perceptions of the ease of use and usefulness shaping the user's intention to adopt a technology. Findings from this study suggest the importance of integrating social influence with TAM in future studies to determine how significant others shape perceptions of technology. It recognises that a farmer's decision to adopt SFT is influenced by others in their network. This perspective is supported by several authors who determine the importance of the farmer's network in sharing knowledge, enabling observation and facilitating sense checking with regarding to technology adoption on-farm (Chavas and Nauges, 2020; Joffre *et al.*, 2020; Pathak *et al.*, 2019).

7.5 Managerial Implications

There are several implications for multiple stakeholders involved in the agriculture sector in particular policymakers, knowledge extension agents and SFT vendors.

7.5.1 Policymaker Implications

As PIIT is a crucial construct in terms of behavioural intention and also building perceptions regarding SFT, educational initiatives are necessary to develop personal innovativeness in farmers. This is also important for farmer technology networks and projects, such as DEMETER, who play an important role in bringing farmers and policymakers together. Investment is required from these actors to build and deliver workshops and training sessions, specifically focusing on the categories of SFT and allowing farmers to interact and test these technologies. These should be run with farmers, farm advisors and SFT vendors on-farm to ensure there is adequate trust in those delivering the initiatives. These programmes should be tailored to various skills, ensuring that they are accessible to farmers with differing levels of personal innovativeness. Furthermore, as discussed in Section 5.8, female farmers had a lower self-reported level of personal innovativeness, thus gender-specific workshops may be worthwhile to further facilitate learning. Using pilot schemes on farm would be an effective strategy to encourage farmers to test the various technologies and improve their overall comfort level and curiosity in experimenting with new technologies. The initiatives should also focus on demonstrating the PEOU of SFT and more importantly the PU in terms of the three pillars of sustainability.

Research from Walder *et al.* (2019) determines that education is a key driver of farmers' innovativeness but equally investment support is critical to allow farmers to experiment with new technology, without worrying about the economic impact. Thus, financial assistance, particularly for smaller-scale farmers in developing PIIT is necessary. Farmers in this study indicated that they would slightly prefer financial assistance to use SFT over financial reward for investing in them. Knierim *et al.* (2018) outlined that tax incentives and government subsidies are a positive influence on adoption. This highlights the pivotal role that government and lending institutions have to play in enabling technology adoption. This support could be in the form of grants, subsidies, tax-breaks, low-interest loans or investment in education and training.

As noted, the large majority of farmers in this research believed that farm advisors and farmers' associations were not sufficiently knowledgeable about SFT. Therefore, investment in educating these stakeholders is critical to allow effective diffusion of knowledge to farmers. This could be done through certification courses with established agricultural colleges or institutions who are experts in the field. This would ensure standardised education related to the benefits of SFT, how to operate SFT, using the data it generates and how to successfully integrate SFT with other technologies on farm. Policymakers also have a role in strengthening the relationship between farmers and agricultural extension services to facilitate effective knowledge dissemination. This could be achieved through the development of open discussion forums where farmers, farm advisors and farming associations can share knowledge, queries and concerns related to SFT.

7.5.2 Knowledge Extension Agent Implications

As outlined previously, farm advisors and farmers' associations, as knowledge extension agents, have an important role in diffusing information on SFT to farmers. This necessitates that these actors possess sufficient knowledge and skills to communicate the benefits of SFT with farmers. Thus, continued education and training is necessary. Additionally, universities and research institutions need to foster the development of personal innovativeness in farmers, ensuring there is adequate real-life experimentation with SFT. Engaging the younger generation of farmers with tailored programmes throughout their education could create a long-term shift towards innovation in farming. Highlighting how SFT can deliver economic and social sustainability should also be part of these educational programmes. This is important for a sector that has an ageing population and therefore needs to attract a younger cohort (Eistrup *et al.*, 2019).

Moreover, the advice given to farmers needs to focus on specific farm needs and be tailored according to the personal innovativeness, farm size and age of the farmer. For example, as outlined in Section 5.8, for older farmers an increase in the PU of SFT leads to a more pronounced increase in BI. Thus, tailoring information to farmers based on their context could lead to increased levels of intention to adopt. In addition, given the position of farm advisors and farmers' associations within the network, they are in an ideal position to facilitate the sharing of success stories of SFT implementation, particularly related to PU. Hosting peer farmer knowledge exchange initiatives with regard to SFT would be a worthwhile initiative. They could also facilitate mentorship where innovative farmers, or those scoring high on PIIT, can help less innovative farmers see the benefits of SFT implementation.

7.5.3 SFT Vendor Implications

As discussed, PU of SFT was an influential factor in the behavioural intention to adopt the technology. Therefore, emphasis needs to be placed on the benefits of SFT in relation to job performance. For SFT vendors, this firstly means prioritising the utility of their technologies when in development, in order to maximise job efficiency for farmers. Incorporating features that directly address farmers' needs can further enhance the PU of SFT. Consequently, co-designing with farmers is an important step in the development process to understand farmers' needs and concerns (Kenny and Regan, 2021). In terms of the marketing strategies of SFT vendors, creating tailored case studies and communication materials which highlight the actual return on investment, savings related to reduced inputs, improved yield, improved decision-making and time saved through automation is essential. As peer farmers in particular were deemed the most influential actors in the network, it would be important to include real farmers in these case studies and testimonials to further highlight real-world examples. Field days, demonstration events, social media marketing and video marketing should all form part of the vendor's marketing strategy to engage farmers accordingly.

Findings determined that the perceived usefulness of SFT increased trust in the SFT vendor. This again highlights the importance of vendors demonstrating the utility and associated benefits of SFT usage. However, SFT vendors should be careful not to over-emphasise the benefits as this could break down the level of trust, as highlighted by Khanna *et al*. (2021). Open and honest communication regarding the capabilities and limitations of SFT is important to foster strong relationships between farmers and vendors (Khanna *et al.*, 2021). Actively seeking feedback from farmers can further strengthen the trust relationship. As highlighted in this study, trust comprised competency and integrity dimensions, therefore, SFT vendors should create tailored marketing strategies that focus on both dimensions of trust.

7.6 Limitations of the Research

This study provides scholarly insight into the factors influencing the behavioural intention to adopt SFT. The findings are, however, shaped by the researcher, the research design, the methodology and the sample size, all of which can impact the reliability, validity and generalisability of the results. Consequently, the limitations of the research are addressed and discussed.

First, the research focused on examining the factors influencing the behavioural intention to adopt SFT. Although several behavioural models determine that there is a linear relationship between behavioural intention and adoption, as outlined in Section 2.8.1, it was not possible to study actual adoption due the limitations of time. In addition, although the research investigated the category of SFT rather than an individual technology, it is still related to the use of smart technology in an agricultural context. Therefore, generalisation of the results to other contexts or sectors should be done with caution.

The non-experimental design followed could have resulted in selection bias which may impact the reliability of the results. Sample representation may be an issue due to the use of a web-based survey. Older farmers, or farmers with limited technical knowledge or limited access to the internet, may have been excluded. It is acknowledged that this could result in a sample that is not entirely representative of the farming population. Furthermore, as self-reporting was used in the data collection, the possibility of overreporting and underreporting of results must be acknowledged. This is a criticism of using TAM, in general, as a theoretical framework in terms of its reliance on self-reported data. Farmers may have been influenced by social desirability bias to answer questions in a favourable rather than truthful manner. In addition, although attention was given to the design of the survey to minimise the practice of satisficing, it is also recognised that respondents may have engaged in the practice.

The research was funded by DEMETER, the Horizon 2020 project which aimed to increase the use of SFT by farmers across Europe. Furthermore, the researcher was working within the project in a marketing context. A quantitative approach was followed, based on the researcher’s philosophical stance and to reduce the influence of personal or project-related biases on the research process. Additionally, respondents were informed that the research was funded by the project. However, it is acknowledged that researcher confirmation bias or funding bias, albeit unknowingly, could still have been present.

The final sample related to 217 responses of which 91% were from Ireland. Initially, it was hoped that there would be a higher response rate from farmers outside Ireland, given the access to European parties in the DEMETER network. However, due to constraints of time and resources, it was not possible to translate the survey into other languages. Furthermore, translating content related to attitudes and behaviours carries several risks, as the translations need to capture both the language as well as cultural and contextual nuances. Consequently, the results are heavily skewed towards Irish farmers, which may impact generalisability to other regions. Nonetheless, the perspectives from farmers outside of Ireland, although in the minority, contribute to the richness of the data.

Although 217 responses resulted in a reasonable sample size, and power of the sample was confirmed as discussed in Section 5.5.4, a larger sample size would have further enhanced the reliability and validity of the results. A wider range of statistical tests and more complex analyses could have been conducted, resulting in a richer analysis. For example, conducting comparative analysis by the farmer’s age or education level, would have been possible without losing statistical power. Cross validation, which is a form of data resampling to assess generalisability (Berrar, 2019), could have been conducted to estimate the true prediction error of the model. It should be noted, however, that model fit testing was conducted to minimise the model error. Furthermore, a larger sample size would have allowed for cluster analysis, grouping farmers into segments based on their characteristics and perceptions, enabling split-sample validation.

Finally, the range of variables that could potentially influence the behavioural intention to adopt SFT is broad. The focus of this research was to examine the key influences, therefore other variables could have been included in this research. For example, culture was identified as a potential influence but was too vast to examine. In addition, farm type which is cited as an influential factor was also difficult to examine due to a large percentage of the farmers who responded being involved in mixed farming.

Taking into consideration the limitations discussed, potential future research avenues are outlined further in the next section.

7.7 Future Research Agenda

This doctoral study examined the factors which influence the farmer's behavioural intention to adopt SFT, thereby advancing knowledge in the area. However, several avenues for future research are evident, given the findings but also the limitations of the research. These potential areas for future research items are discussed in more detail below.

First, as this research examined the behavioural intention to adopt SFT, a longitudinal study focusing on actual adoption as the outcome variable would significantly enhance scholarly understanding. Focusing on non-adopters, early adopters and experienced users of SFT at different intervals across a longer timescale would allow for a more comprehensive assessment of SFT adoption and usage. The longitudinal study would help with understanding the different phases of adoption, as outlined by Rogers (2003). It would also offer more insight into cause-and-effect relationships between variables.

Second, this model was developed to be generalisable, focusing on the category of Smart Farming Technology, rather than a specific technology. Further research would be welcome to determine if the results can be replicated in other contexts and settings. These studies would examine the intention to adopt smart technology in contexts such as the agri-food supply chain or micro-enterprises, as an example.

As discussed in the limitations of the study, the use of a web-based survey may have alienated older and less tech-savvy farmers. Using a mixed-method approach, combining a web-survey with traditional methods such as a postal survey or face to face interviews might be more accessible to an older cohort of farmers. Engaging with local agricultural communities and attending local farming events to administer the survey or conduct interviews could result in increased participation. Furthermore, it would enable discussion or clarification on any of the topics or terminology discussed.

Findings from the research indicate that perceived usefulness was a key factor influencing the BI to adopt SFT. However, PEOU was not a significant influence either on the PU of SFT or the BI to adopt SFT. Future research could focus on identifying and creating new measurement items that are relevant to PU and PEOU in a smart technology context. The original items used to measure PU and PEOU from Davis (1989) related to the adoption of four technologies in the workplace namely electronic mail, a file editor called XEDIT and two specific graphic systems technologies in the workforce. It is argued that the application of smart technologies to various industries has a greater impact on overall operations than the task-specific use of the technologies studied under TAM. Thus, creating new measurement items for PU and PEOU to reflect the distinct requirements of smart technology would be an interesting avenue to examine. Additionally, it would be beneficial to examine the behavioural intention to adopt smart technologies in other sectors to understand if the diminished role of PEOU is unique to SFT.

The results from the study highlighted the importance of personal innovativeness as a trait in influencing both the PU and BI to adopt SFT. Future research could focus on determining what encourages personal innovativeness and how to create effective strategies to develop it as a personality trait. Furthermore, people who are classified as innovators or scoring high on innovativeness are more likely to be exposed to mass media and rely less on information from interpersonal sources when adopting a technology (Rogers, 2003). According to Yi *et al.* (2006b) there are insufficient empirical studies that assess the relationship between social influence and PIIT. A review of the literature continues to highlight a scarcity of studies in this domain. The significant impact of social influence on perceived usefulness was determined in this study. Thus, further research into the influence of the farmer's network on the personal innovativeness of the farmer would be welcomed. Determining how knowledge is disseminated within the network and how it can improve the PIIT of farmers would add a significant contribution to the literature.

The research also highlighted that limited role of farm advisors in encouraging SFT implementation. Further research could investigate farmers' perceptions of the credibility and relevance of advice regarding SFT from advisors. In addition, from a policy point of view, research could be conducted to examine how current agricultural policies and frameworks support or hinder advisors in promoting SFT.

In this study, trust in the SFT vendor was examined and results demonstrated that PU influenced trust. This contradicted seminal studies from Gefen *et al.* (2003) and Pavlou (2003) which, it was argued, may be due to the population of interest and the conceptualisation and operationalisation of trust. Consequently, future research could examine if trust in the vendor changes over time, focusing on both initial trust and continued trust and its influence on BI and PU. Initial trust forms during the user's initial interactions or early experiences with trust over time developing based on continued experience (Cabiddu *et al.*, 2022). Future research avenues could also focus on clarifying the operationalisation of trust. Interpersonal trust was examined in this study but institutional-based trust from a sociological perspective would also be interesting to study further. Furthermore, hypothesising a bi-directional relationship between trust and PU would be a considerable area to examine. Thus, a longitudinal study would enable further examination of the role and influence of trust.

Finally, this research focused on the individual characteristics of the farmer and their perceptions of, and attitude towards using, SFT. However, the issue of cost was evident in both the open-ended questions and when respondents were asked to rank the barriers to adoption, which cannot be ignored. This is consistent with many studies that find cost to be a major impacting factor on the intention to adopt SFT (Blasch *et al.*, 2022; Daberkow and McBride, 2003; Long *et al.*, 2016). Further research could explore the impact of cost on the intention to adopt SFT. The initial purchase cost, ongoing maintenance costs and training costs should be considered.

7.8 Conclusion

This research examined the key influences of farmers' behavioural intentions to adopt SFT. This chapter focused on summarising the research process and the research findings. Perceived usefulness and personal innovativeness had a significant effect on the behavioural intention to adopt SFT. PIIT also influenced PEOU and PU, with the relationship with ease of use being stronger. Social influence had a positive influence on the PU of SFT, demonstrating the importance of the farmer's network, and in particular, peer farmers in facilitating knowledge exchange. Trust in the SFT vendor was influenced by PU which again highlighted the importance of vendors developing products that make a considerable improvement to on-farm operations in terms of increased job efficiency, effectiveness and output. The theoretical contributions in advancing TAM were then discussed. The main theoretical contribution was the successful integration of key antecedent variables (personal innovativeness, social influence and trust) and moderating variables (farm size and age) to increase the explanatory and predictive power of TAM. Further theoretical contributions in generalising the model to alternative contexts were discussed as was the declaration that the construct items of TAM need to be updated to reflect the sophistication of technologies in an artificial intelligence era. A number of managerial implications for policymakers, knowledge extension agents and SFT vendors were presented. Finally, the limitations of the research were acknowledged, and potential future research agendas were outlined.

In conclusion, the primary objective of this doctoral study was to investigate the effect of key factors which influence the farmer's behavioural intention to adopt SFT. The significance of this study is underscored by the potential of SFT to increase agricultural sustainability in a sector faced with several challenges. The study addresses many of the calls for further research in the domain, given the low and fragmented rate of SFT adoption. The findings provide new insights into the importance of perceived usefulness and personal innovativeness in encouraging SFT adoption. Social influence and trust in the SFT vendor are also successfully incorporated with TAM, demonstrating their influence in shaping perceptions and in the technology intention adoption process.

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Appendix A Overview of Qualitative Interviews

The eight interviews with farmers took place online, in January and February 2022, using the Zoom platform. Table A.1 outlines an overview of the respondents. On average, the interviews lasted forty-five minutes. Interviews were conducted in English, at a time suitable for interviewees. All respondents were provided with a detailed information sheet and signed a consent form, indicating their willingness to participate in the interview. The interviews were recorded with the consent of the respondents, transcribed and analysed using NVivo12. Respondents were from four different countries: Ireland, Italy, Georgia, and Romania. Three respondents were female while five were male. Three were dairy farmers, one was a beef farmer, one a sheep farmer, one was involved in grape production and the remaining two were crop farmers (soybean, wheat, barley, corn). Two respondents were non-adopters, while six were currently using SFT on farm. This suggested that using SFT experience as a control variable would be meaningful. Both non-adopters and adopters agreed that SFT is beneficial. The SFT used varied across autonomous tractors, wearables, robotic milkers, smart irrigation systems, weather sensors and variable rate fertilizer technology. Interviewees differed in their description of SFT, which highlighted the need to be very clear in the questionnaire when explaining the terminology. Capturing data related to the type of technology being used currently, and those the farmer intended on adopting in the future, would be necessary also.

Respondent ID	Age	Gender	Farm Type	Farm location	Full Time (FT)/ Part Time (PT)
1	45	M	Sheep	Ireland	PT
2	40	M	Dairy	Ireland	FT
3	42	M	Beef to calf	Ireland	PT
4	32	F	Dairy	Ireland	FT
5	24	F	Dairy	Ireland	FT
6	35	M	Arable	Romania	FT
7	28	M	Vine Growing	Georgia	PT
8	26	F	Arable	Italy	FT

Table A.1 Overview of interview respondents

The interviews provided support for the use of TAM as a theoretical framework for the research. Usefulness of the technology was the key priority for all farmers. They differed in their assessment of usefulness, but it mainly related to increased production, labour savings and the reduced use of inputs. Ease of Use was also important with two farmers, for example, explaining that they returned a particular technology as it was too complicated to use. Education and age were highlighted as influencing Ease of Use with all interviewees explaining they had some form of training which they felt gave them confidence to use the technology. It was also stated that, for many, their parents would not be comfortable using these technologies. Farmers differed in their rate of adoption of SFT based on their farm size and farm type. This supported the use of age, education and farm size as moderating variables. In addition, all farmers mentioned the situational context of the war in the Ukraine as a key factor influencing their future adoption of technologies. This was due to savings or capital that may have been set aside for investing in technology now being used to combat rising prices on fertilizers and herbicides. A ranking question was added to survey to capture how this might influence farmers.

Personality was an interesting area to explore with differing personality traits arising from each of the respondents. Farmers were slightly uncomfortable discussing their personality traits but happy to discuss their own level of innovativeness using technology. This confirmed that although using the Big Five personality dimensions would be interesting, it might result in farmers leaving the survey due to potential discomfort. A more generic measure of personality such as personal innovativeness in the IT domain would be more relevant to this study.

In terms of social influence, peer farmers were seen as the most trusted source of information regarding SFT. Respondents differed on the influence of farm advisors. Some farmers felt that advisors were not sufficiently educated on new technologies, while others felt their farm advisors played an important role in technology adoption. This discrepancy resulted in the operationalisation of individualised measurements of social influence in the questionnaire as well as a generic measure.

Trust was an important discussion point in all interviews, highlighting the need for its inclusion in the conceptual model. All respondents were trusting of the technology but varied in their trust level of the technology provider. Therefore, trust was operationalised as Trust in the SFT vendor. Some farmers questioned the providers' ability to solve problems with the technology, while other farmers felt they were being over-promised to. In summary, the interviews help to operationalise the constructs in the survey and also helped with wording the questions, using a lexicon familiar to farmers.

Appendix B Original Scales and Modified Scales used in the research

Table B.1 Original Scales and Modified Scales

Factors influencing the farmer's behavioural intention to adopt SFT		
Construct	*Original Item*	*Measurement Item*
Personal Innovativeness in the domain of Information Technology taken from Agarwal and Prasad (1998)	• If I heard about a new information technology, I would look for ways to experiment with it. • Among my peers, I am usually the first to try out new information technologies. • In general, I am hesitant to try out new information technologies (R). • I like to experiment with new information technologies.	• If I heard about a new technology, I would look for ways to experiment with it. • Among my peers, I am usually the first to explore new technologies. • In general, I am hesitant to try out new technologies (R). • I like to experiment with new technologies.
Social Influence adopted from Venkatesh *et al.* (2003)	• People who influence my e think that I should use the system. • People who are important to me think that I should use the system.	• People who influence my behaviour would think that I should use Smart Farming Technology. • People who are important to me would think that I should use Smart Farming Technology.
Perceived Ease of Use adopted from Davis (1989)	• Learning to operate <technology> would be easy for me. • I would find it easy to get <technology> to do what I want it to do. • My interaction with <technology> would be clear and understandable. • I would find <technology> to be flexible to interact with. • It would be easy for me to become skillful at using <technology> • In general, I would find <technology> easy to use.	• In general, learning to operate Smart Farming Technology would be easy for me. • In general, I would find it difficult to get Smart Farming Technology to do what I want it to do (R). • In general, my interaction with Smart Farming Technology would be clear and understandable. • In general, I would find Smart Farming Technology to be flexible to interact with. • In general, it would be difficult for me to become skillful at using Smart Farming Technology (R).

		• In general, I would find Smart Farming Technology easy to use.
Perceived Usefulness adopted from Davis (1989)	• Using <technology> in my job would enable me to accomplish tasks more quickly. • Using <technology> would improve my job performance. • Using <technology> in my job would increase my productivity • Using <technology> in my job would enhance my effectiveness on the job. • Using <technology> would make it easier to do my job. • I would find <technology> useful in my job.	• In general, using Smart Farming Technology would enable me to accomplish tasks more quickly. • In general, using Smart Farming Technology would improve my job performance. • In general, using Smart Farming Technology would increase my productivity. • In general, using Smart Farming Technology would reduce my effectiveness on the job. (R) • In general, using Smart Farming Technology would make it harder to do my job. (R) • In general, I would find Smart Farming Technology useful in my job.
Trust (Integrity) adopted from McKnight *et al.* (2002)	• I am comfortable relying on Internet vendors to meet their obligations. • I feel fine doing business on the Internet since Internet vendors generally fulfill their agreements. • I always feel confident that I can rely on Internet vendors to do their part when I interact with them.	• I would be comfortable relying on SFT vendors to meet their obligations. • I would feel fine doing business with SFT vendors since they generally fulfil their agreements. • I would feel confident that I can rely on SFT vendors to do their part when I interact with them.
Trust (Competency) adopted from McKnight *et al.* (2002)	• In general, most Internet vendors are competent at serving their customers. • Most Internet vendors do a capable job at meeting customer needs.	• In general, most SFT vendors are competent in their field. • Most SFT vendors do a capable job at meeting farmers' needs.

	• I feel that most Internet vendors are good at what they do.	• I feel that most SFT vendors are good at what they do.
Trust (Benevolence) adopted from McKnight *et al.* (2002)	• I feel that most Internet vendors would act in a customers' best interest. • If a customer required help, most Internet vendors would do their best to help. • Most Internet vendors are interested in customer well-being, not just their own well-being.	• I feel that most SFT vendors would act in a farmer's best interest. • If a farmer required help, most SFT vendors would do their best to help. • Most SFT vendors are interested in farmers' well-being, not just their own well-being.
Propensity to Trust adopted from Mayer and Davis (1999)	• In general, people really do care about the well-being of others. • The typical person is sincerely concerned about the problems of others. • Most of the time, people care enough to try to be helpful, rather than just looking out for themselves. • In general, most folks keep their promises. • I think people generally try to back up their words with their actions. • Most people are honest in their dealings with others. • I believe that most professional people do a very good job at their work. • Most professionals are very knowledgeable in their chosen field. • A large majority of professional people are competent in their area of expertise. • I usually trust people until they give me a reason not to trust them. • I generally give people the benefit of the doubt when I first meet them.	• In general, people really do care about the well-being of others. • The typical person is sincerely concerned about the problems of others. • Most of the time, people care enough to try to be helpful, rather than just looking out for themselves. • In general, most people keep their promises. • I think people generally try to back up their words with their actions. • Most people are honest in their dealings with others. • I believe that most professional people do a very good job at their work. • Most professionals are very knowledgeable in their chosen field. • A large majority of professional people are competent in their area of expertise. • I usually trust people until they give me a reason not to trust them. • I generally give people the benefit of the doubt when I first meet them.

	• My typical approach is to trust new acquaintances until they prove I should not trust them.	• My typical approach is to trust new acquaintances until they prove I should not trust them.
Attitude adopted from Davis (1986); Taylor and Todd (1995) and Ajzen (2001).	• Using the <technology> is a (bad/good) idea. • I (dislike / like) the idea of using the <technology>. • Using the <technology> would be: (unpleasant/pleasant). • Using the <technology> is a (foolish / wise) idea.	• In general, using Smart Farming Technology would be a good idea. • In general, I like the idea of using Smart Farming Technology. • In general, using Smart Farming Technology would be unpleasant (R) • In general, using Smart Farming Technology would be wise.
Behavioural Intention adopted from Venkatesh (2000). Venkatesh *et al.* (2003)	• Assuming I had access to the system, I intend to use it. • Given that I had access to the system, I predict that I would use it.	• I intend to use Smart Farming Technology in the future. • Assuming I had access to Smart Farming Technology, I predict that I would use it.

Appendix C Questionnaire administered

Adoption of Smart Farming Technology Survey

Survey Overview

Hello,

My name is Grainne Dilleen and I am currently undertaking a PhD at South East Technological University, Ireland to examine the factors which influence farmers' intention to adopt Smart Farming Technology (SFT). This study is funded by the EU project, DEMETER.

Your participation in this survey is voluntary and will make a valuable contribution to the research. It should take approximately 10 minutes to complete. All data collected will be anonymised. Findings will be presented in aggregate form so that no individual responses can be identified.

All participants will be entered into a draw to win a €100 Amazon voucher. To participate in the draw, please enter your email address at the end of the survey. Any duplicate responses or Spam responses will be disqualified. If you have any queries about the research, please contact me at grainne.dilleen@postgrad.wit.ie

Kind Regards,
Grainne

I agree to participate in this research:

- ◯ Agree and read background to the study.
- ◯ Agree and start the survey.
- ◯ Exit.

Adoption of Smart Farming Technology Survey

Research Details

The aim of this research is to get a better understanding of the key internal and external factors which influence farmers' intention to adopt Smart Farming Technology (SFT). It also seeks to understand the relationship between these factors. Your responses to this survey are very important and will provide an understanding of the current adoption level of SFT and the drivers and barriers to adoption. Participation is entirely voluntary.

SFT is information and communication technology incorporated into farm machinery and on farm, creating large amounts of data which the farmer can use to optimise operations. Examples include farm management information systems, robotic milking machines, precision agriculture systems, global navigation satellite systems, wireless networks, drones, sensors, autonomous tractors, smart collars, artificial intelligence. Some examples are illustrated below:

The research is funded under DEMETER, the Horizon 2020 project, which aims to drive the digitisation of the European agrifood sector.

All data collected will be anonymised, remain strictly confidential and will only be accessible by the researcher. Findings will be presented in aggregate form so that no individual responses can be identified. The researcher will use the data you provide only for the purposes set out above and will, at all times, comply with the General Data Protection Regulation. All data will be destroyed after twelve months. If you have provided your email address, it will not be shared with any third party.

Please contact the researcher if you have any further queries or if you would like to get a copy of the research results following publication.

Regards,

Grainne Dilleen
grainne.dilleen@postgrad.wit.ie

Adoption of Smart Farming Technology Survey

Farming Background

In what farming sector(s) are you active? Please tick all that apply.

- ☐ Beef
- ☐ Beekeeping/Apiculture
- ☐ Cereals and Crops
- ☐ Dairy
- ☐ Fruit
- ☐ Pigs
- ☐ Poultry
- ☐ Sheep
- ☐ Vegetables
- ☐ Other (please specify)

What is the size of your farm, in hectares?

<2	2-10	10-20	20-50	50-100	100-500	>500
◯	◯	◯	◯	◯	◯	◯

What is your primary role on the farm?

- ◯ Farm Owner
- ◯ Farm Manager
- ◯ Farm family employee
- ◯ Other (please specify)

What is the legal status of the farm that you work on?

- ◯ Family farm or family company/partnership
- ◯ Company without family shareholder (i.e., corporation)
- ◯ Cooperative farm (i.e., farmer-owned and run enterprise)
- ◯ Other (please specify)

Are you a full-time or part-time (i.e., have another job off-farm) farmer?

- ◯ Full-time
- ◯ Part-time

As outlined, Smart Farming Technology includes Farm Management Information Systems (e.g., software systems for collecting, processing and storing data), precision agriculture and/or global navigation satellite systems (e.g., remote sensing technology, sensors, decision support systems, wireless networks, etc.) and autonomously operating machines (e.g., drones, robotics, machine learning, artificial intelligence, etc.).

On a scale of 1 (Strongly disagree) to 7 (Strongly agree), please rate your level of agreement/disagreement with the following statement:

	Strongly disagree	Disagree	Somewhat disagree	Neither disagree nor agree	Somewhat agree	Agree	Strongly agree
I have previous experience of using Smart Farming Technology.	○	○	○	○	○	○	○

What category of Smart Farming Technology are you using? Please tick all that apply.

- ☐ Farm Management Information Systems (e.g., software systems for collecting, processing and storing data).
- ☐ Precision Agriculture and/or Global Navigation Satellite Systems (e.g., remote sensing technologies, sensors, decision support systems, wireless networks, etc.).
- ☐ Autonomously operating machines (e.g., drones, robotics, machine learning, artificial intelligence, etc.).
- ☐ None

The following questions aim to understand your intention to adopt any Smart Farming Technology in the future. On a scale of 1 (Strongly disagree) to 7 (Strongly agree), please rate your level of agreement/disagreement with the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I intend to use Smart Farming Technology in the future.	◯	◯	◯	◯	◯	◯	◯
Assuming I had access to Smart Farming Technology, I predict that I would use it.	◯	◯	◯	◯	◯	◯	◯

What would encourage you to adopt Smart Farming Technology? Please rank each item in order of importance, with no. 1 as the 'most important' item, to no. 6 as the 'least important' item.

- Technologies that are more straightforward to use
- Financial Assistance (e.g., grants and subsidies)
- Financial Reward
- Governmental policies/legislation
- Improved digital infrastructure (e.g., broadband)
- Specialised education and training

Are there other factors which would encourage you to adopt Smart Farming Technology?

What would stop you from adopting Smart Farming Technology? Please rank each item in order of importance, with no. 1 as the 'most important' item, to no. 6 as the 'least important' item.

- The cost of buying Smart Farming Technology
- Data privacy concerns
- Lack of technical knowledge
- Lack of integration of technologies
- No clear return on investment
- Rising cost of inputs (e.g., fertilizer, energy)

Are there other factors which would stop you from adopting Smart Farming Technology?

Smart Farming Technology Usefulness and Ease of Use

The following questions aim to understand how you feel regarding the usefulness of Smart Farming Technology. On a scale of 1 (Strongly disagree) to 7 (Strongly agree), please rate your level of agreement/disagreement with the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In general, using Smart Farming Technology would enable me to accomplish tasks more quickly.	○	○	○	○	○	○	○
In general, using Smart Farming Technology would improve my job performance.	○	○	○	○	○	○	○
In general, using Smart Farming Technology would increase my productivity.	○	○	○	○	○	○	○
In general, using Smart Farming Technology would reduce my effectiveness on the job.	○	○	○	○	○	○	○
In general, using Smart Farming Technology would make it harder to do my job.	○	○	○	○	○	○	○
In general, I would find Smart Farming Technology useful in my job.	○	○	○	○	○	○	○

The following questions aim to understand how you feel regarding the ease of use of Smart Farming Technology. On a scale of 1 (Strongly disagree) to 7 (Strongly agree), please rate your level of agreement/disagreement with the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In general, learning to operate Smart Farming Technology would be easy for me.	○	○	○	○	○	○	○
In general, I would find it difficult to get Smart Farming Technology to do what I want it to do.	○	○	○	○	○	○	○
In general, my interaction with Smart Farming Technology would be clear and understandable.	○	○	○	○	○	○	○
In general, I would find Smart Farming Technology to be flexible to interact with.	○	○	○	○	○	○	○
In general, it would be difficult for me to become skillful at using Smart Farming Technology.	○	○	○	○	○	○	○
In general, I would find Smart Farming Technology easy to use.	○	○	○	○	○	○	○

The following questions aim to understand your overall attitude to Smart Farming Technology. On a scale of 1 (Strongly disagree) to 7 (Strongly agree), please rate your level of agreement/disagreement with the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In general, using Smart Farming Technology would be a good idea.	○	○	○	○	○	○	○
In general, I like the idea of using Smart Farming Technology.	○	○	○	○	○	○	○
In general, using Smart Farming Technology would be unpleasant.	○	○	○	○	○	○	○
In general, using Smart Farming Technology would be wise.	○	○	○	○	○	○	○

Adoption of Smart Farming Technology Survey

Your Farming Network

The following questions relate to the influence that others may have on your adoption of Smart Farming Technology. On a scale of 1 (Strongly agree) to 7 (Strongly disagree), please rate your level of agreement/disagreement with the following statements:

	Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree
People who influence my behaviour would think that I should use Smart Farming Technology.	○	○	○	○	○	○	○
People who are important to me would think that I should use Smart Farming Technology.	○	○	○	○	○	○	○
Farmers that I know would think that I should use Smart Farming Technology.	○	○	○	○	○	○	○
Generally speaking, I want to do what farmers I know think I should do.	○	○	○	○	○	○	○
My family members would think that I should use Smart Farming Technology.	○	○	○	○	○	○	○
Generally speaking, I want to do what my family members think I should do.	○	○	○	○	○	○	○

On a scale of 1 (Strongly agree) to 7 (Strongly disagree), please rate your level of agreement/disagreement with the following statements. If the question is not relevant to you, please tick N/A.

My farm advisor would think that I should use Smart Farming Technology.

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	N/A
○	○	○	○	○	○	○	○

Generally speaking, I want to do what my farm advisor thinks I should do.

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	N/A
○	○	○	○	○	○	○	○

My farm advisor is knowledgeable about Smart Farming Technology.

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	N/A
○	○	○	○	○	○	○	○

The farmers' association that I am a member of would think that I should use Smart Farming Technology.

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	N/A
○	○	○	○	○	○	○	○

Generally speaking, I want to do what my farmers' association thinks I should do.

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	N/A
○	○	○	○	○	○	○	○

My farmers' association is knowledgeable about Smart Farming Technology.

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	N/A
○	○	○	○	○	○	○	○

The farm cooperative that I am a member of would think that I should use Smart Farming Technology. (A farm cooperative in this context is a farmer-owned and run enterprise where resources are pooled to increase productivity).

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	N/A
○	○	○	○	○	○	○	○

Generally speaking, I want to do what my farm cooperative thinks I should do.

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	N/A
○	○	○	○	○	○	○	○

The farm cooperative that I am a member of is knowledgeable about Smart Farming Technology.

Strongly agree	Agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Disagree	Strongly disagree	N/A
○	○	○	○	○	○	○	○

Adoption of Smart Farming Technology Survey

Smart Farming Technology vendors/providers

The following questions relate to your opinion of companies that sell Smart Farming Technology, otherwise known as SFT vendors. On a scale of 1 (Strongly disagree) to 7 (Strongly agree), please rate your level of agreement/disagreement with the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I feel that most SFT vendors would act in a farmer's best interest.	○	○	○	○	○	○	○
If a farmer required help, most SFT vendors would do their best to help.	○	○	○	○	○	○	○
Most SFT vendors are interested in farmers' well-being, not just their own well-being.	○	○	○	○	○	○	○
I would be comfortable relying on SFT vendors to meet their obligations.	○	○	○	○	○	○	○
I would feel fine doing business with SFT vendors since they generally fulfill their agreements.	○	○	○	○	○	○	○
I would feel confident that I can rely on SFT vendors to do their part when I interact with them.	○	○	○	○	○	○	○
In general, most SFT vendors are competent in their field.	○	○	○	○	○	○	○
Most SFT vendors do a capable job at meeting farmers' needs.	○	○	○	○	○	○	○
I feel that most SFT vendors are good at what they do.	○	○	○	○	○	○	○

The following questions relate to your general trusting beliefs, they are not related specifically to SFT vendors. On a scale of 1 (Strongly disagree) to 7 (Strongly agree), please rate your level of agreement/disagreement with the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
In general, people really do care about the well-being of others.	○	○	○	○	○	○	○
The typical person is sincerely concerned about the problems of others.	○	○	○	○	○	○	○
Most of the time, people care enough to try to be helpful, rather than just looking out for themselves.	○	○	○	○	○	○	○
In general, most people keep their promises.	○	○	○	○	○	○	○
I think people generally try to back up their words with their actions.	○	○	○	○	○	○	○
Most people are honest in their dealings with others.	○	○	○	○	○	○	○
I believe that most professional people do a very good job at their work.	○	○	○	○	○	○	○
Most professionals are very knowledgeable in their chosen field.	○	○	○	○	○	○	○
A large majority of professional people are competent in their area of expertise.	○	○	○	○	○	○	○
I usually trust people until they give me a reason not to trust them.	○	○	○	○	○	○	○
I generally give people the benefit of the doubt when I first meet them.	○	○	○	○	○	○	○
My typical approach is to trust new acquaintances until they prove I should not trust them.	○	○	○	○	○	○	○

Adoption of Smart Farming Technology Survey

Personality and Demographics

The following questions relate to your assessment of yourself. On a scale of 1 (Strongly disagree) to 7 (Strongly agree), please rate your level of agreement/disagreement with the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
If I heard about a new technology, I would look for ways to experiment with it.	○	○	○	○	○	○	○
Among my peers, I am usually the first to explore new technologies.	○	○	○	○	○	○	○
In general, I am hesitant to try out new technologies.	○	○	○	○	○	○	○
I like to experiment with new technologies.	○	○	○	○	○	○	○

What age bracket are you in?

- ○ 18-24
- ○ 25-34
- ○ 35-44
- ○ 45-54
- ○ 55-64
- ○ 65 and over

What gender do you identify as?

- ○ Woman
- ○ Man
- ○ Non-binary
- ○ Prefer not to state
- ○ Prefer to self-describe

What is the highest level of education that you have completed?

- ◯ No formal education
- ◯ Primary certificate / Junior School/ Elementary School
- ◯ Secondary certificate / High School
- ◯ Bachelor degree
- ◯ Master degree/Postgraduate
- ◯ PhD
- ◯ Other (please specify)

How many years have you been farming?

- ◯ Up to 5 years
- ◯ 5-10 years
- ◯ 11-25 years
- ◯ Over 25 years

In what country do you live?

When do you intend on adopting Smart Farming Technology in the future?

- ◯ Never
- ◯ In the next year
- ◯ In the next 3 years
- ◯ In the next 5 years
- ◯ In more than 5 years

What category of Smart Farming Technology do you intend on adopting in the future? Please tick all that apply.

- ☐ Farm Management Information Systems (e.g., software systems for collecting, processing and storing data).
- ☐ Precision Agriculture and/or Global Navigation Satellite Systems (e.g., remote sensing technologies, sensors, decision support systems, wireless networks, etc.).
- ☐ Autonomously operating machines (e.g., drones, robotics, machine learning, artificial intelligence, etc.).
- ☐ None

For verification purposes, please enter the first 3 letters of your surname and the 4 digits of today's date. E.g. JOH0112

Is there anything else related to the adoption or use of Smart Farming Technology that you would like to add?

Please add your email address if you would like to be entered in the draw for a €100 Amazon Voucher.

Appendix D Samples of online and print articles promoting the survey

IRISH FARMERS JOURNAL

SEARCH

BEEF DAIRY SHEEP AGRIBUSINESS MACHINERY TILLAGE PEDIGREE BUILDINGS PROPERTY

Farmer views on use of smart farming technology wanted

The survey is focused on examining the influences on a farmer's intention to adopt smart farming technology.

Amy Forde
NEWS > NEWS
15 January 2023

The survey is open to all farmers, regardless of age, farm size, farm type and location. \ David Ruffles

Farmers are being asked to fill out a survey on their attitudes towards smart farming technology.

Examples of smart farming include software systems for collecting and storing data, remote sensing technology and drones and robotics.

This survey is focused on examining the influences on a farmer's intention to adopt smart farming technology and it is part of a PhD being undertaken by Grainne Dilleen, researcher at South East Technological University.

Figure D.1 Online article from Irish Farmers' Journal promoting the survey

(01) 426 8900
facebook.com/macranafeirme
www.twitter.com/macranafeirme
www.macra.ie

echnology

Farmers using smart irrigation technology in the EU-funded project, DEMETER.

SFT survey

The research also tells us that there is a relationship between age and adoption of SFT. Young farmers have a higher probability of being interested in technology and adopting it, while older farmers are less interested and thus less likely to adopt SFT.

New generations of farmers are learning about precision agriculture and SFT from an early stage. Therefore, if we can continue to merge their passion of farming with technology, it can be a positive step towards ensuring the resilience of the agriculture sector in the 21st century.

Researcher at South East Technological University (SETU) and Macra Skillnet Steering committee member Grainne Dilleen is conducting a PhD to further examine the factors influencing SFT adoption. She is looking for farmers, regardless of farm size, farm type or level of technology use, to complete her survey. It should take approximately 10 minutes and all information will be stored and analysed anonymously.

➲ Please scan the QR code or visit https://www.surveymonkey.com/r/DEM22 to start the survey.

➲ Email grainne.dilleen@postgrad.wit.ie with any queries.

Figure D.2 Article in Irish Farmers' Journal written on behalf of Macra Na Feirme

Researcher seeks input on factors influencing farmers' adoption of Smart Farming Technology

on March 1, 2023

Grainne Dilleen, a researcher at South East Technological University in Ireland, is conducting a Ph.D study to investigate the internal and external factors that influence farmers' intention to adopt Smart Farming Technology (SFT). Specifically, she is interested in the role of trust in technology providers and the influence of the farmer's network on the adoption decision.

According to Grainne, the use of digital technologies and SFT can contribute to the sustainability of the agriculture sector across the three pillars of the environment, economy, and society. However, to take the first step towards this goal, it is essential to understand the attitudes, motivations, and perceptions of farmers regarding these technologies.

The survey is open to all farmers worldwide, regardless of the type, size, location, or use of technology on their farms. Completing the survey should take no more than 10 minutes, and all responses will remain confidential and analyzed anonymously.

Grainne looks forward to hear from potato farmers worldwide, and encourages anyone interested to access and complete the survey here: https://www.surveymonkey.com/r/POT23.

Grainne can be reached at grainne.dilleen@postgrad.wit.ie for further information.

Figure D.3 Online article in Potato News Today

Appendix E Outlier Tests

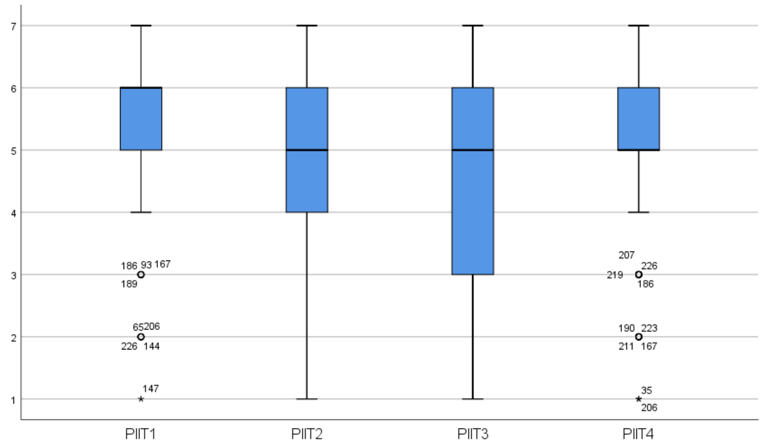

Figure E.1 Personal Innovativeness Outlier Test

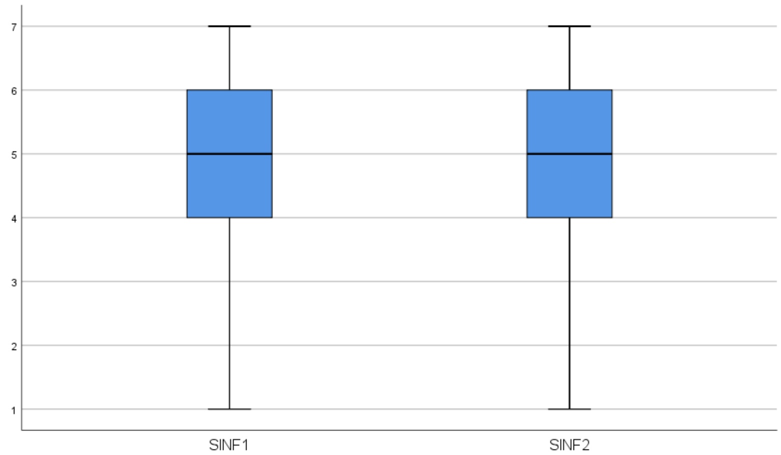

Figure E.2 Social Influence Outlier Test

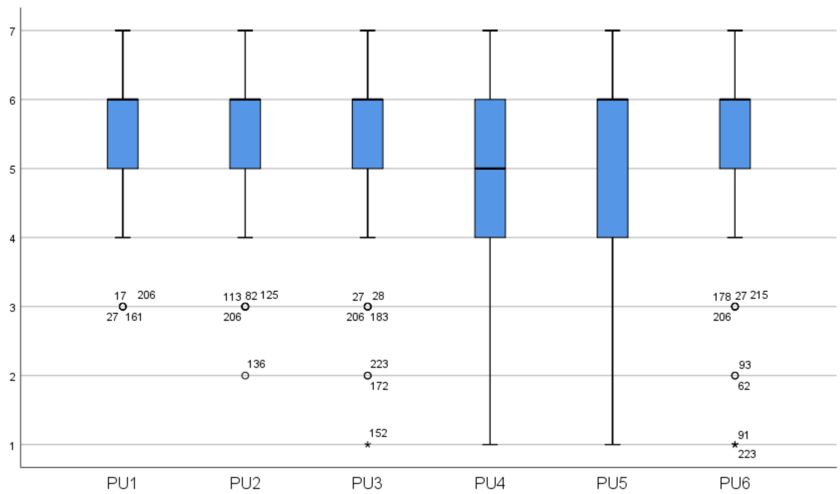

Figure E.3 Perceived Usefulness Outlier Test

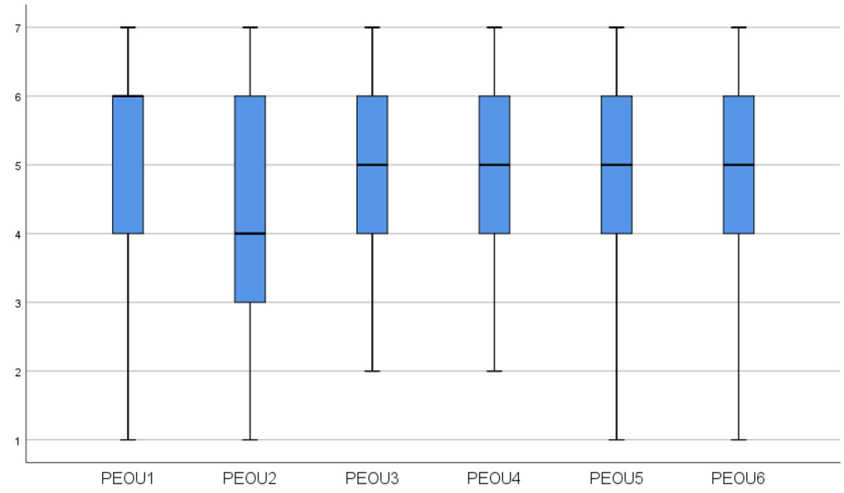

Figure E.4 Perceived Ease of Use Outlier Test

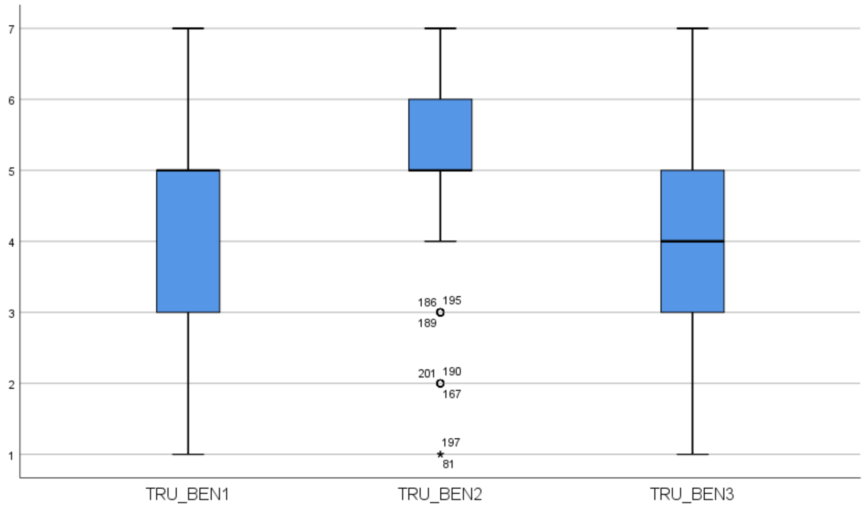

Figure E.5 Trust (Benevolence) Outlier Test

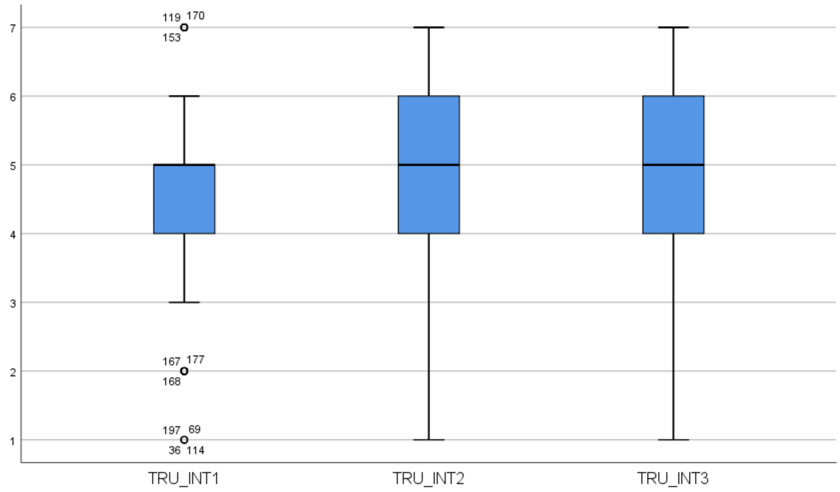

Figure E.6 Trust (Integrity) Outlier Test

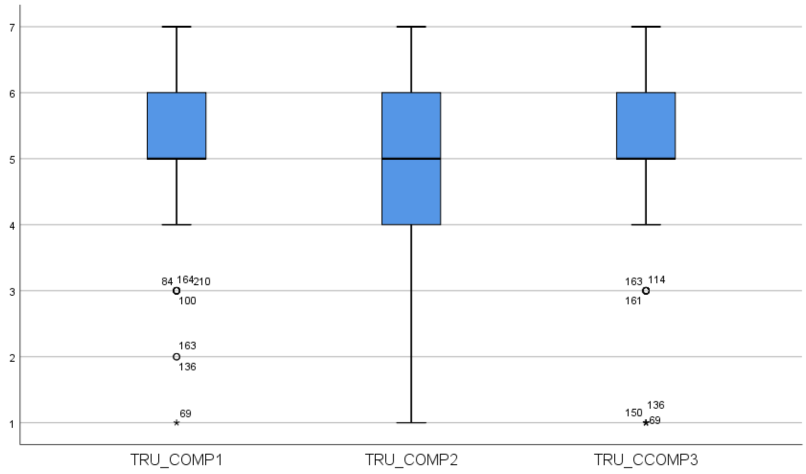

Figure E.7 Trust (Competency) Outlier Test

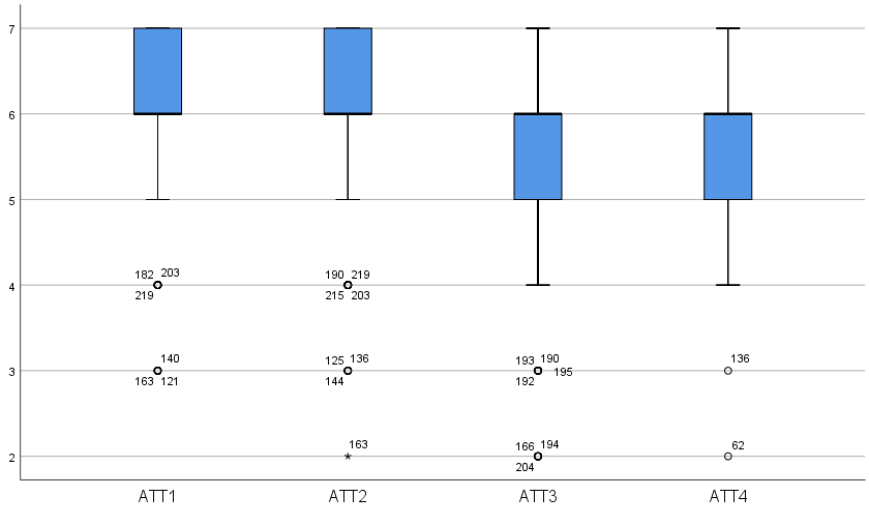

Figure E.8 Attitude Outlier Test

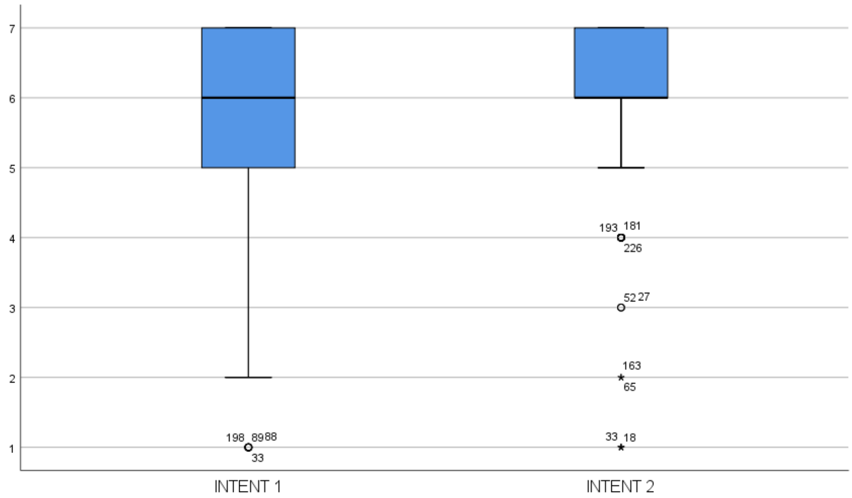

Figure E.9 Behavioural Intention Outlier Test

Appendix F Test for normality of each construct

F.1 Q-Q Plots for all constructs

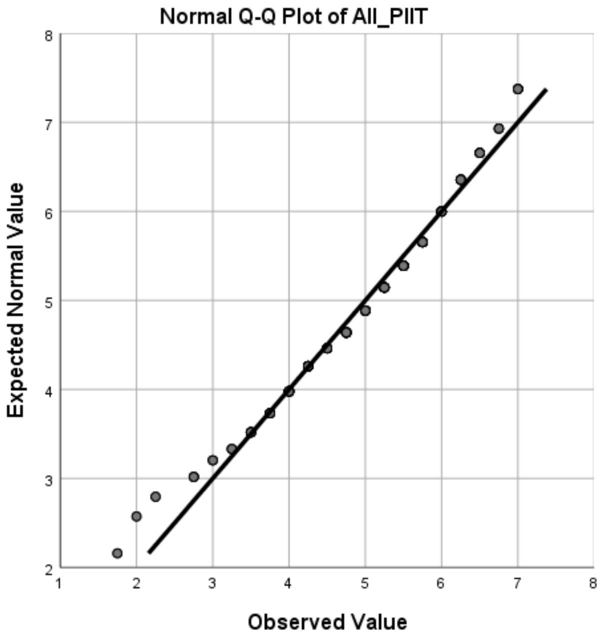

Figure F.1 Test for Linearity for Personal Innovativeness in IT

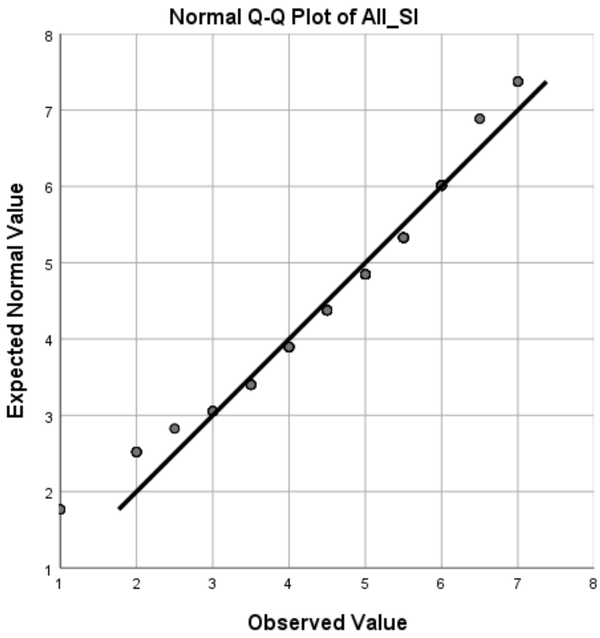

Figure F.2 Test for Linearity for Social Influence

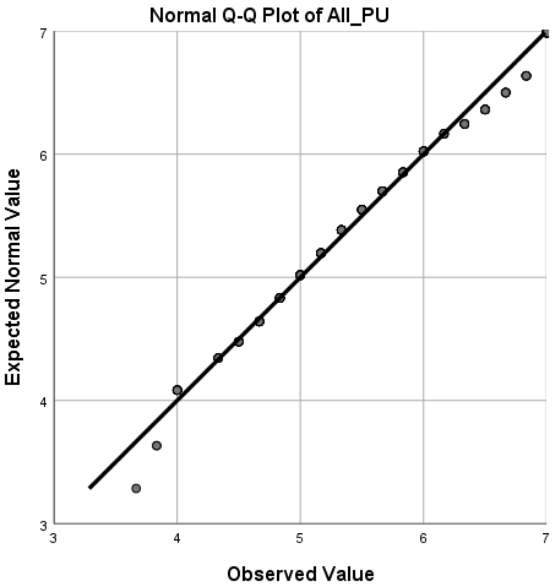

Figure F.3 Test for Linearity for Perceived Usefulness

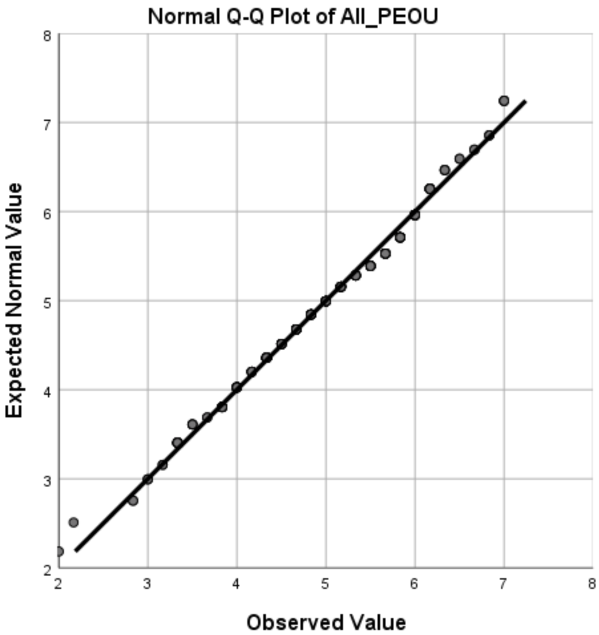

Figure F.4 Test for Linearity for Perceived Ease of Use

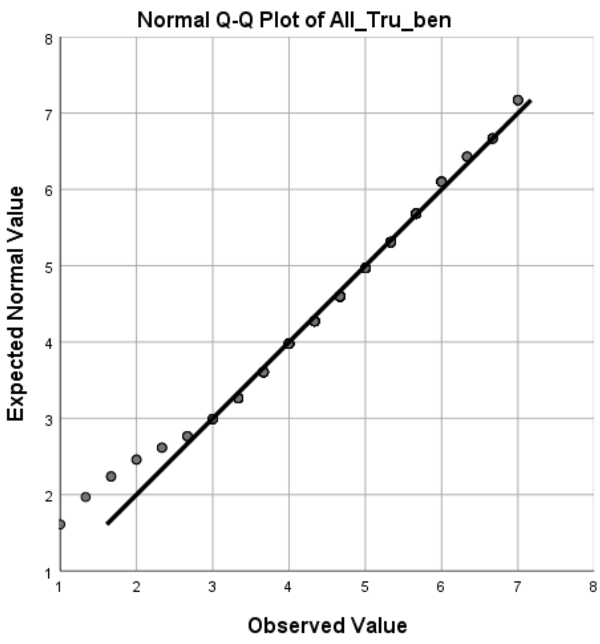

Figure F.5 Test for Linearity for Trust in SFT Vendor (Benevolence)

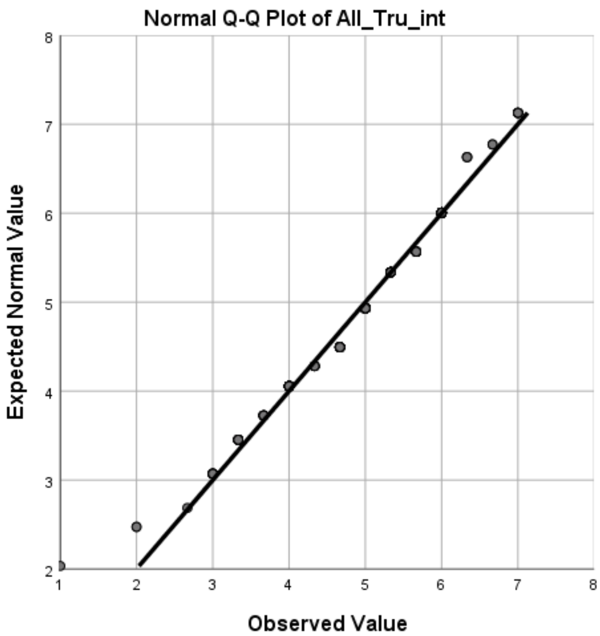

Figure F.6 Test for Linearity for Trust in SFT Vendor (Integrity)

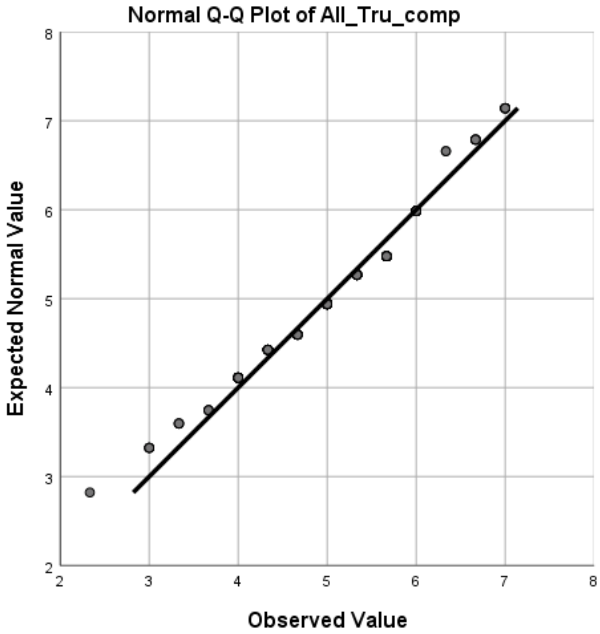

Figure F.7 Test for Linearity for Trust in SFT Vendor (Competency)

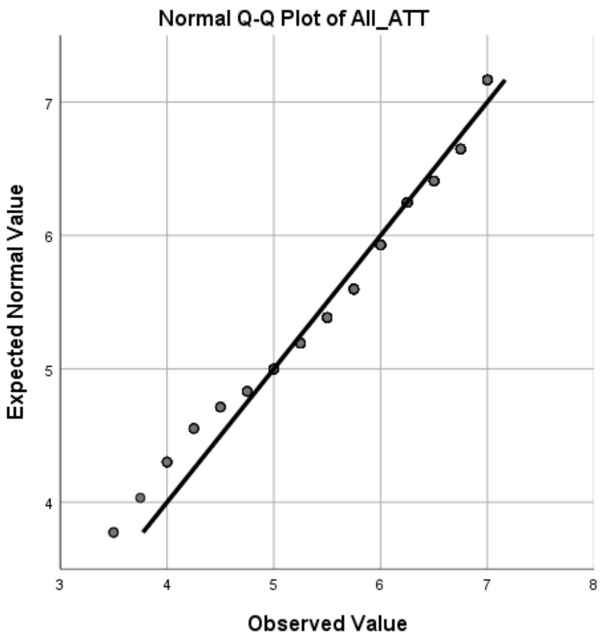

Figure F.8 Test for Linearity for Attitude

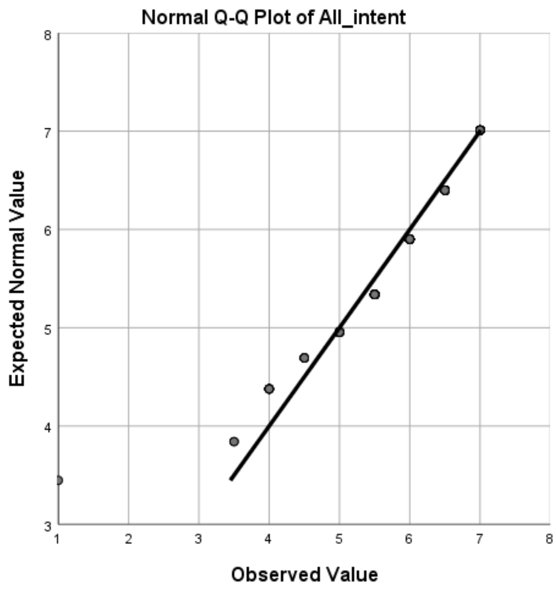

Figure F.9 Test for Linearity for Behavioural Intention

F.2 Histograms for all constructs

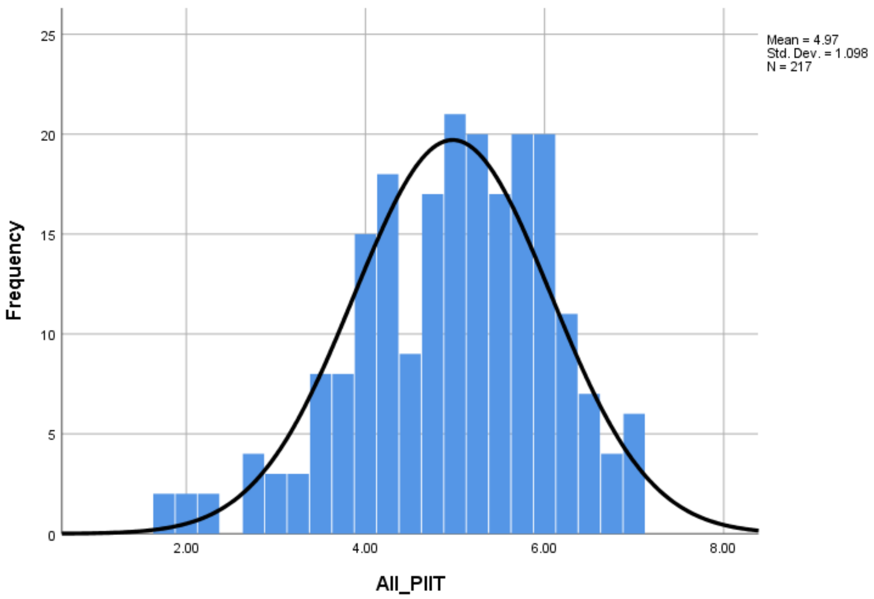

Figure F.10 Test for normality of data for Personal Innovativeness in IT

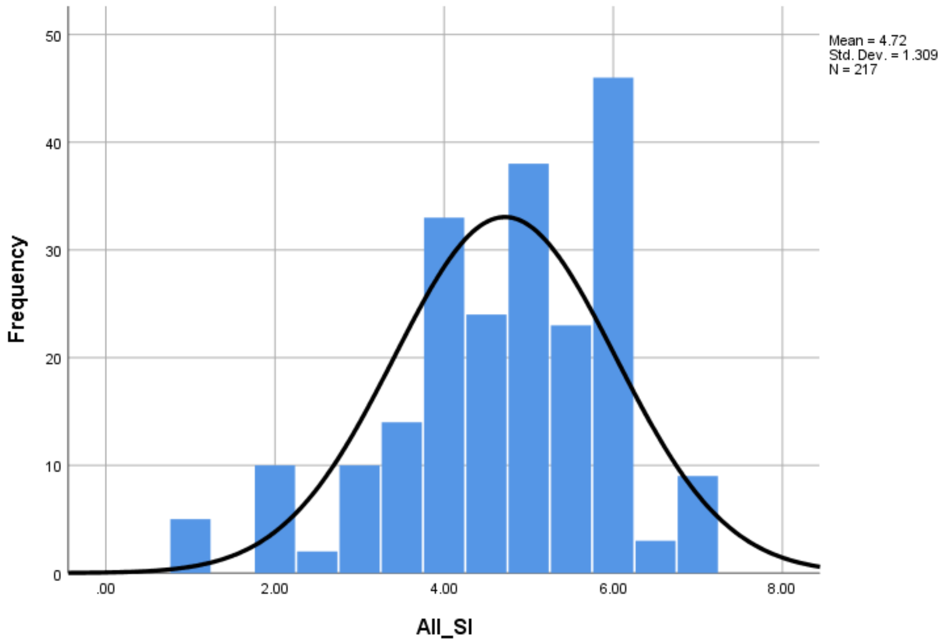

Figure F.11 Test for normality of data for Social Influence

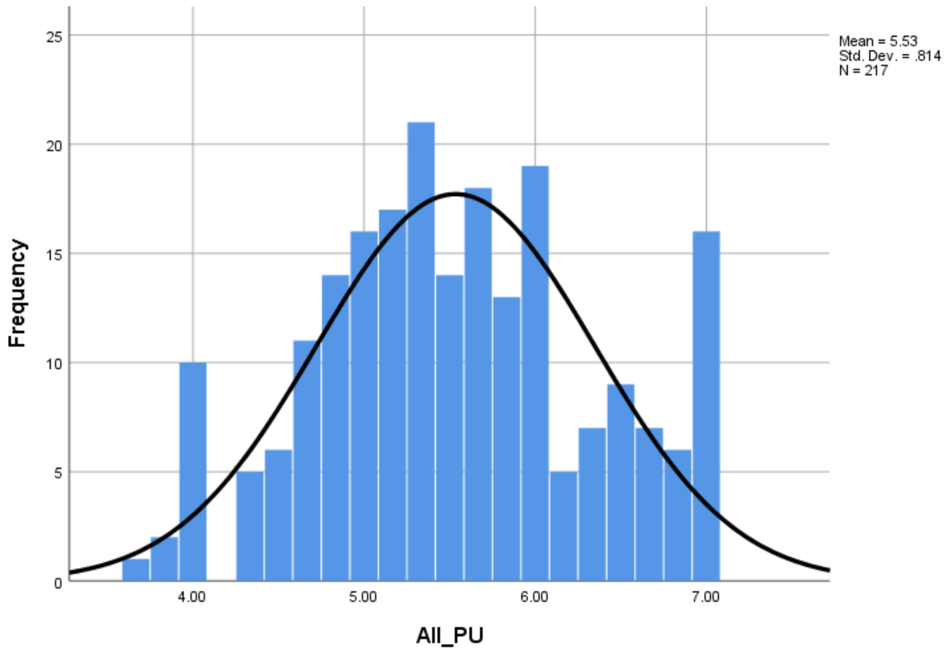

Figure F.12 Test for normality of data for Perceived Usefulness

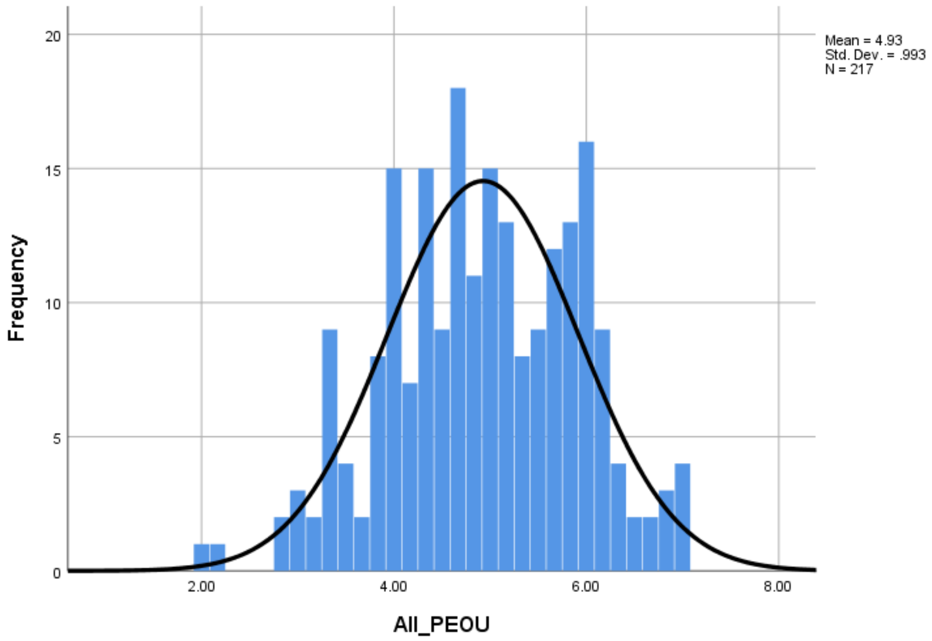

Figure F.13 Test for normality of data for Perceived Ease of Use

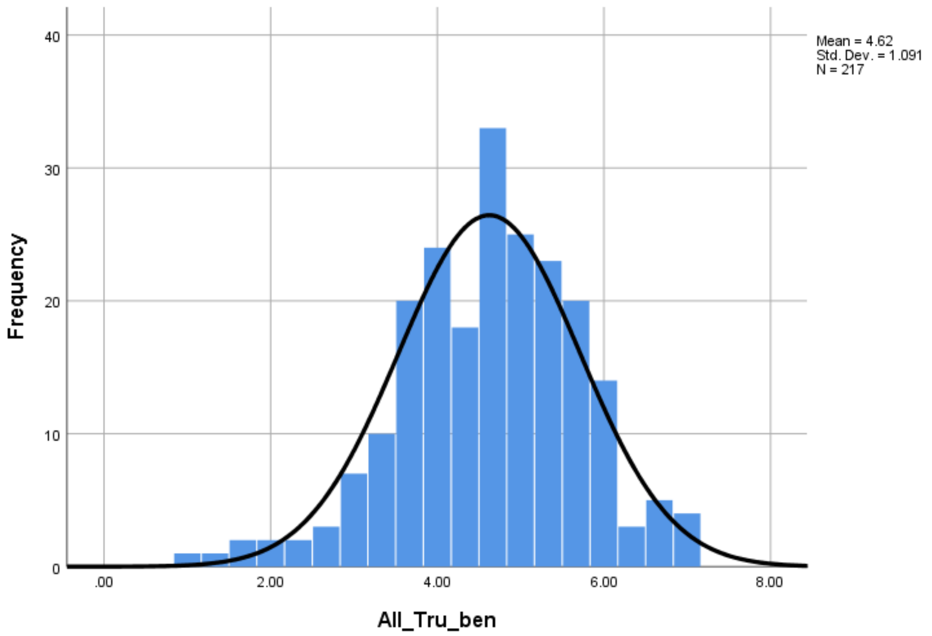

Figure F.14 Test for normality of data for Trust in SFT Vendor (Benevolence)

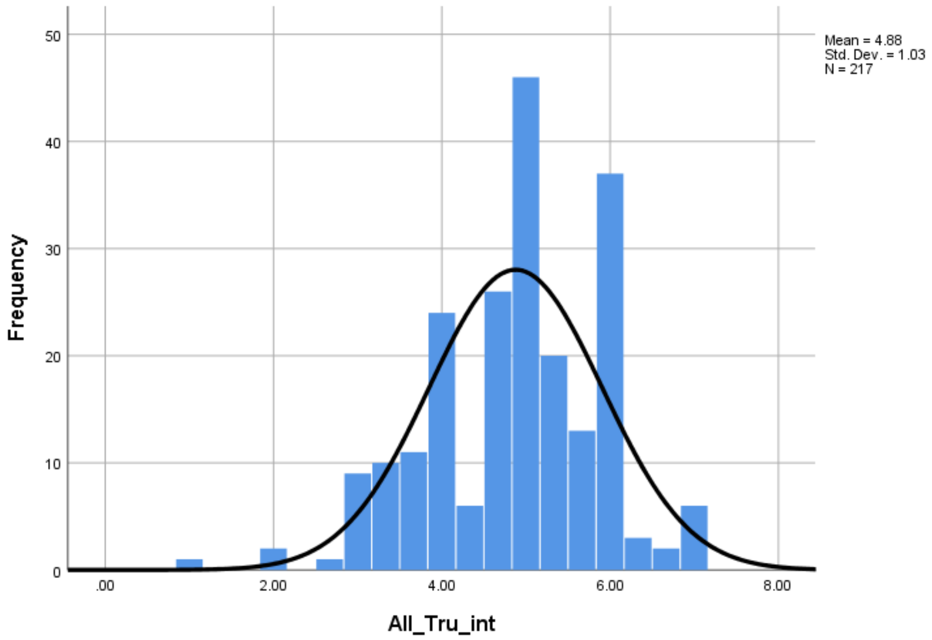

Figure F.15 Test for normality of data for Trust in SFT Vendor (Integrity)

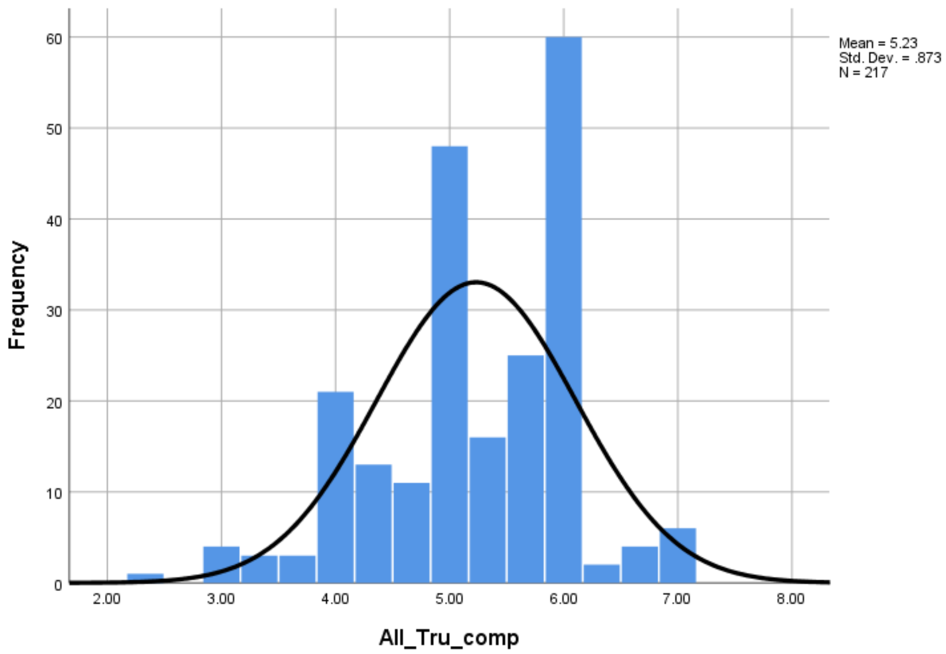

Figure F.16 Test for normality of data for Trust in SFT Vendor (Competency)

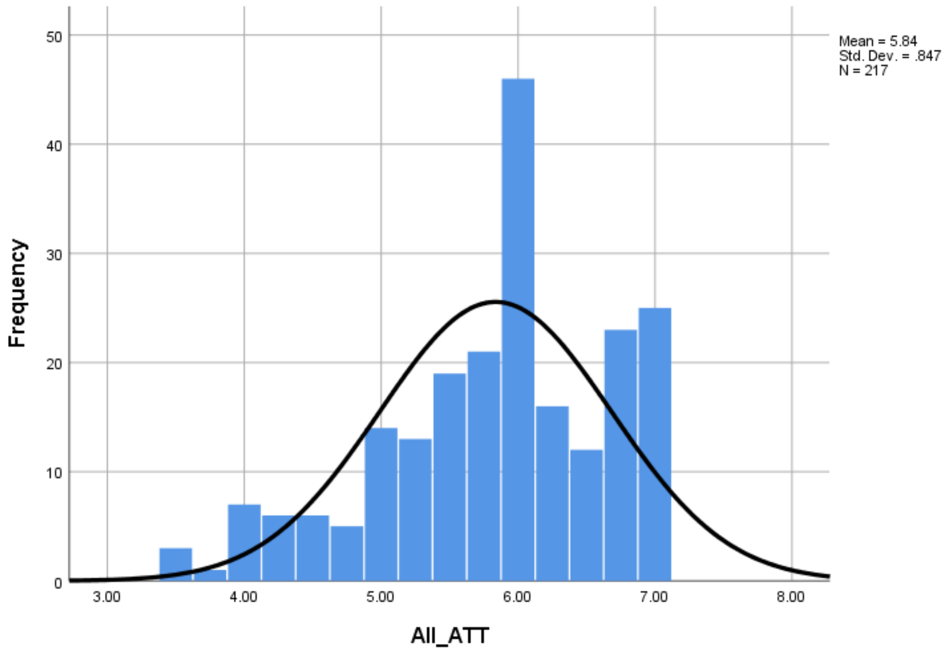

Figure F.17 Test for normality of data for Attitude

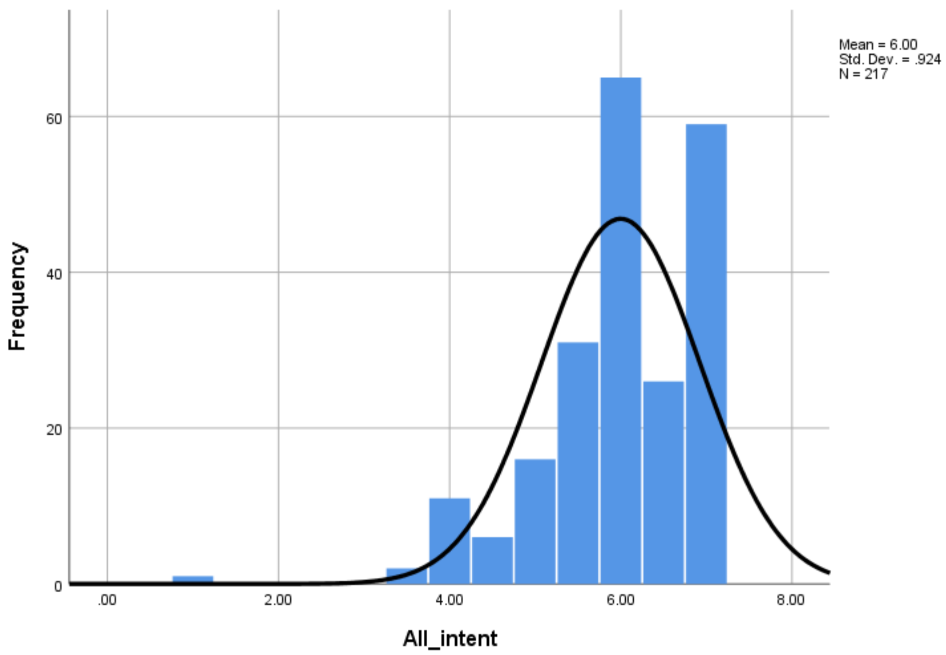

Figure F.18 Test for normality of data for Behavioural Intention

Table F.1 Skewness and Kurtosis figures for all items

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
INTENT 1	217	1	7	5.89	1.103	-1.525	.165	4.000	.329
INTENT 2	217	1	7	6.10	.981	-1.602	.165	4.141	.329
PU1	217	3	7	5.71	.965	-.377	.165	-.517	.329
PU2	217	2	7	5.75	1.029	-.644	.165	.099	.329
PU3	217	1	7	5.70	1.066	-.927	.165	1.728	.329
PU4	217	1	7	4.92	1.594	-.507	.165	-.838	.329
PU5	217	1	7	5.35	1.339	-.712	.165	-.052	.329
PU6	217	1	7	5.79	1.059	-1.479	.165	3.950	.329
PEOU1	217	1	7	5.18	1.421	-.859	.165	.077	.329
PEOU2	217	1	7	4.30	1.471	-.019	.165	-.985	.329
PEOU3	217	2	7	5.02	1.128	-.495	.165	.027	.329
PEOU4	217	2	7	4.93	1.180	-.317	.165	-.315	.329
PEOU5	217	1	7	4.99	1.540	-.707	.165	-.491	.329
PEOU6	217	1	7	5.13	1.264	-.796	.165	.232	.329
ATT1	217	3	7	6.02	.918	-1.088	.165	1.406	.329
ATT2	217	3	7	6.00	.940	-1.122	.165	1.138	.329
ATT3	217	2	7	5.55	1.250	-1.072	.165	.676	.329
ATT4	217	2	7	5.77	.954	-.752	.165	.503	.329
SINF1	217	1	7	4.67	1.440	-.557	.165	-.221	.329
SINF2	217	1	7	4.76	1.406	-.775	.165	.372	.329
TRU_BEN1	217	1	7	4.41	1.376	-.370	.165	-.522	.329
TRU_BEN2	217	1	7	5.07	1.236	-.964	.165	.869	.329
TRU_BEN3	217	1	7	4.39	1.357	-.292	.165	-.364	.329
TRU_INT1	217	1	7	4.60	1.298	-.551	.165	-.042	.329
TRU_INT2	217	1	7	4.98	1.101	-.824	.165	1.050	.329
TRU_INT3	217	1	7	5.05	1.088	-.659	.165	.461	.329
TRU_COMP1	217	2	7	5.29	.930	-.645	.165	.231	.329
TRU_COMP2	217	2	7	5.18	.964	-.409	.165	-.148	.329
TRU_CCOMP3	217	1	7	5.22	1.008	-.977	.165	1.749	.329
PIIT1	217	2	7	5.37	1.073	-.903	.165	.932	.329
PIIT2	217	1	7	4.65	1.452	-.342	.165	-.500	.329
PIIT3	217	2	7	4.67	1.578	-.238	.165	-1.249	.329
PIIT4	217	1	7	5.20	1.275	-.982	.165	.724	.329
Valid N (listwise)	217								

Appendix G Factors and Barriers influencing SFT adoption

Table G.1 Factors influencing SFT adoption

Are there any other factor which would influence your adoption of SFT
1. advantages and benefits of use 2. recording of 'field' data for assistance with management systems (ie data from cows, gps, motion sensors, etc)
Accurate fertiliser spreading
Added value for small farms
All captured
Allow better decision making
Any affordable technology that saves time as I farm part-time
Anything that will save time/ reduce workload.
Awareness of available products
Being more sustainable
Better for sustainability and the environment.
Better integration between systems with open APIs to allow for user controlled customisation with better control of the data thats collect and sent back to the manufacturer
Better prices for farm produce to justify paying for new technology.
Clear advice/guidance on the benefits of their use.
Compatibility with existing smart technology systems Ease of data uploading to database/excel
cost
Cost and benefits of it
Currently cost prohibitive for small farmers
Data compatibility - among ag machine producers and service providers. Availability of open data (e.g. LPIS - field boundaries, soil maps)
Durability of the product
Easier farming methods
Education
Efficiency is number one. Most farmers will use anything if it saves them money and reduces work load
Environmental
Environmental impact of tech
Examples of other farmers using the same technology.
Fair competion between companies -i.e only allowed use Pasturebase for grass recording !
Friends advice
Further research into the benefits to livestock
Good return on investment and reduced cost of software - not having to have huge acres to justify equipment
have to make workload easier and less cumbersome and repetitive
Help with work on the farm with little complication
If it improves profitability of the farm I'm all for it
Improve efficiencies on my farm.
Improve efficiency on farm. Improve profits and animal welfare.
Improve lifestyle - make it easier to farm.
Improved efficiencies on the farm

improving accuracy when spreading fertilizer
Knowledge of what smart farming tools will add value to my business . Payback has to be rewarded in time / quality of life / bottom line
labour
Labour saving
Labour saving
Labour shortage
Lack of skilled labour makes technology more important for day to day work.
Less labour
Less labour intensive
Make business more financially and environmentally sustainable
Making work simpler and more efficient
More intensive farming on larger farms
Necessity
Neighbours of Friends recommending. Or advisor recommending.
No
Not necessarily, but if there were better incentives put in place for farmers, the adoption rate of these new technologies would be much higher. To encourage us to invest in smart farming tech, we need to see a realistic return on investment and how the technology can save us money and time in the long run. Anything which makes farming life easier and more efficient is very much welcome but it has to make sense and be easy to use.
Not that I can think of
proven return on investment including beneficial as far as my time management goes. I'm not investing in something that takes too much of my time or requires a new employee to implement.
Purely cost
Save time
Saving time, measure to manage
Simple and straight forward
Simple, effective and easy to use systems
Social media influencers using Smart farming technology
Software packages that don't need to be changed or updated. A device that will last.
Technology for hill sheep farming needs to be developed, electronic tracking of animals would be extremely beneficial
The precision off the system is very important. GPS controlled fertiliser spreaders I feel I would Use if I was Farming
The size of the machinery and the upkeep of the machine such as services
Those that help the environment. Measuring and verifying the inset and offsets on the farm. So much valuable data on the farm not measured or recognised. Farming gets very bad press but alot of farmers have great pride in the enterprise and try to do things right, even when it comes at a financial penalty or shortfall to them. If SFT could help measure the good parts as well as the areas requiring improvement, everyone would benefit.
Time
Time consuming
time saving
Time saving
Time saving technology

To help with management but currently options available are expensive on a small unit
To improve efficiency
to reduce labour
Try before you buy
Using part-time farmer holdings as pilot R&D test sites.
using something straight forward
Work quality

Table G.2 Barriers influencing adoption of SFT

Any other factor which would stop you from adopting SFT?
Back up support is very important to adopting a new technology. If there's an issue or something you need answered, a resolution needs be happen within a realistic time frame. Unfortunately, automated chat bots or FAQs don't cut it. That personal level of support is needed and 7 days a week depending on what the tech is doing on farm.
Being forced to sync with third party agencies such as ICBF & Teagasc
Cant teach old dogs new tricks,   Older farmers/ family members knock smart farming technology straight away as they were never brought up around it or never seen the advantages.
Colleagues experience
Cost
Cost
Difficulty in its use combined with the risk of being locked into a certain system.
Effectiveness of the product
Farm size
Fear of the unknown/unseen parts of technology.
How long will the technology last ? Cost and frequency of services and maintenance. If I have warranty on the technology, what's to stop the company going out of business? Warranty with a company that has gone bust is no good to me.
How the information gathered is used by Gov agencies i.e. observance of GDPR
If it didn't make financial sense
Lack of access
Lack of backup would be huge. Future proofing. Complicated setup and running systems
lack of demonstration
Lack of knowledge
little or no benefit to work on farm and no improvement to herd or production or profitability
low functionality of machines/sensors for VRA (I mean if it doesn't work as it is promoted by the producer)
More information and discussions necessary to enable person to understand the huge issue of AI and teknol...
No
No time to use or learn how to use
Older generation not willing to move with the times
Poor communication from the sector. E.g. Fert inputs can be reduced by good data collection on farm (soil sampling Yr on Yr tracking and analysis). These types of benefits should be made clear to promote progressive change. Albeit, fert lobby would not be exactly happy with this messaging, but we need to move on from this!

Possibilities of faults/ breakdowns/ cost
Price
Product ease of use
Reliability
Risk of cyber security crime
Security, can it be hacked, particularly if self operating machinery become main stream
Smart technology that actually works. I invested in heat detection system that works very badly and only correct 50% of the time so I end up observing cows more then if I didn’t have one
Speed
Staff not being able to use the technology
Support. Sometimes there is just too much information. Only information that is needed should show. Cost and upkeep of the technology. And service and repairs
Technology becoming outdated too quick
Time constraints I.e. bandwidth to use the technology.
To me a dairy farmer physically works with his animals like a tillage farmer ploughs etc it's what there purpose is robots take all that away so what does a farmer do to serve his purpose as a farmer sit down on the couch pressing buttons to control his robots
word of mouth- poor outcome when used eg. reduced yield, growth

Appendix H Descriptive Statistics Analysis

This appendix provides a comprehensive analysis of the descriptive statistics relating to each of the constructs in the model.

H.1 Personal Innovativeness in Information Technology

As outlined in Section 4.4.3, Personal Innovativeness in Information Technology was measured by four items. Respondents positively agreed with all items. They were more likely to 'look for ways to experiment with new technology if they heard about it', scoring the highest mean (*M*=5.37). Respondents also agreed that they like to experiment with new technologies (*M*=5.20). Respondents indicated that they somewhat agreed that among their peers they are usually the first to experiment with new technologies (*M*=4.57). PIIT3 (In general, I am hesitant to try out new technologies) was reverse coded before analysis. The mean value is 4.47 (±1.578) indicating that respondents somewhat agreed that were not hesitant to use new technologies.

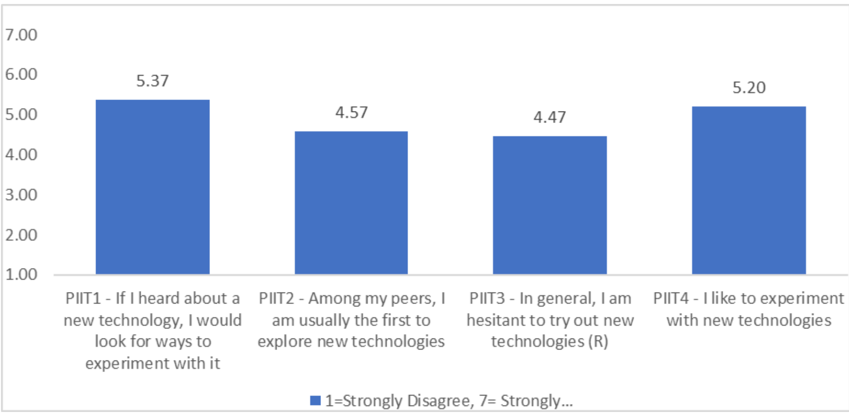

Figure H.1 Personal Innovativeness Average Results

Table H.1 shows the descriptive statistics for Personal Innovativeness. Skewness figures are all within the acceptable range. The negative skewness indicates a greater number of larger values agreeing with the statement. Kurtosis for PIIT3 was >±1, but still in the acceptable range of +/- 7 recommended by Hair *et al*. (2010).

Table H.1 Personal Innovativeness Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PIIT1	217	2	7	5.37	1.073	-.903	.165	.932	.329
PIIT2	217	1	7	4.65	1.452	-.342	.165	-.500	.329
PIIT3	217	2	7	4.67	1.578	-.238	.165	-1.249	.329
PIIT4	217	1	7	5.20	1.275	-.982	.165	.724	.329
Valid N (listwise)	217								

The inter-item correlation, as detailed in Table H.2 between the items in Personal Innovativeness shows there is high correlation between the items.

Table H.2 Personal Innovativeness Inter-Item Correlation

Inter-Item Correlation Matrix

	PIIT1	PIIT2	PIIT3	PIIT4
PIIT1	1.000	.585	.461	.620
PIIT2	.585	1.000	.512	.624
PIIT3	.461	.512	1.000	.562
PIIT4	.620	.624	.562	1.000

As illustrated in Table H.3, the Cronbach's Alpha achieved for Personal Innovativeness is >.70 at .823. No improvement is made to the construct with the removal of any of the items.

Table H.3 Personal Innovativeness Reliability Statistics

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PIIT1	14.52	13.177	.637	.422	.791
PIIT2	15.24	10.750	.675	.479	.765
PIIT3	15.23	10.565	.608	.383	.806
PIIT4	14.69	11.464	.718	.516	.748

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.823	.833	4

As outlined in Table H.4, unidimensionality was obtained and factor loadings are >.40 as recommended by (Hair *et al.*, 1998).

Table H.4 Factoral Validity Personal Innovativeness

	Cronbach's Alpha	**Factor Loadings ****
• If I heard about a new technology, I would look for ways to experiment with it.	**.823**	.718
• Among my peers, I am usually the first to explore new technologies.		.746
• In general, I am hesitant to try out new technologies. (R)		.701
• I like to experiment with new technologies.		.820
****One dimension determined**		

H.2 Social Influence

As outlined in Figure H.2, respondents agreed that people who are important to them and who influence their behaviour would think that they should use SFT. 'People who are important' to respondents were slightly more influential (M = 4.76) than 'People who influence their behaviour' (M = 4.67).

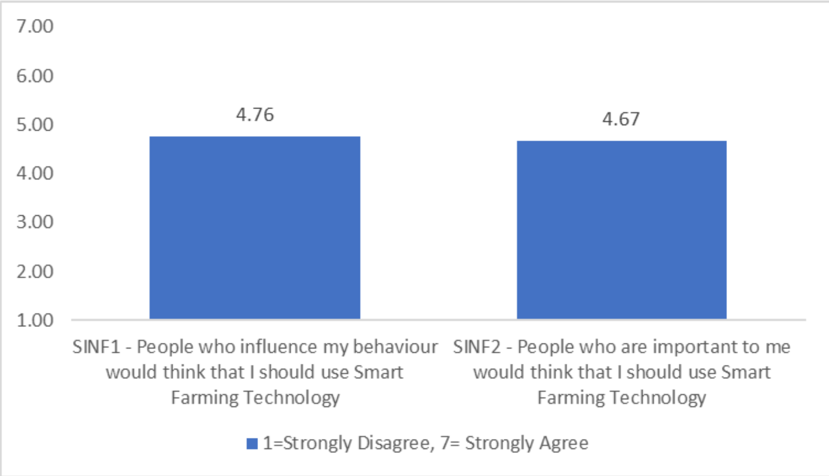

Figure H.2 Social Influence Average Results

As illustrated in Table H.5 below, the figures for skewness and kurtosis are in an acceptable range.

Table H.5 Social Influence Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
SINF1	217	1	7	4.67	1.440	-.557	.165	-.221	.329
SINF2	217	1	7	4.76	1.406	-.775	.165	.372	.329
Valid N (listwise)	217								

Cronbach's Alpha for the Social Influence scale as outlined in Table H.6 suggests a high degree of internal consistency.

Table H.6 Social Influence Reliability Statistics

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
SINF1	4.76	1.977	.694	.481	.
SINF2	4.67	2.073	.694	.481	.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.819	.819	2

The inter-item correlation, as detailed in Table H.7 shows that there is high correlation between the items in Social Influence.

Table H.7 Social Influence Inter-Item Correlation

Inter-Item Correlation Matrix

	SINF1	SINF2
SINF1	1.000	.694
SINF2	.694	1.000

One dimension was obtained, and factor loadings are above the recommended cut-off value of .40 (Hair *et al.*, 1998) as shown in Table H.8.

Table H.8 Factor loadings for Social Influence

	Cronbach's Alpha	**Factor Loadings ****
• People who influence my behaviour would think that I should use Smart Farming Technology.	**.819**	.809
• People who are important to me would think that I should use Smart Farming Technology.		.863
**One dimension determined		

H.3 Perceived Usefulness

Respondents perceived SFT as useful, as indicated in Figure H.3. PU4 and PU5 were reverse coded before analysis. PU1, 2,3 and 6 all scored a similar average, meaning that respondents agreed that SFT is useful, increases productivity, improves job performance, and allows farmers to accomplish tasks more quickly. Respondents somewhat agreed that SFT would increase effectiveness on the job (M = 4.92, ±1.594). Equally, respondents agreed that SFT would make it easier for the farmer to conduct their job.

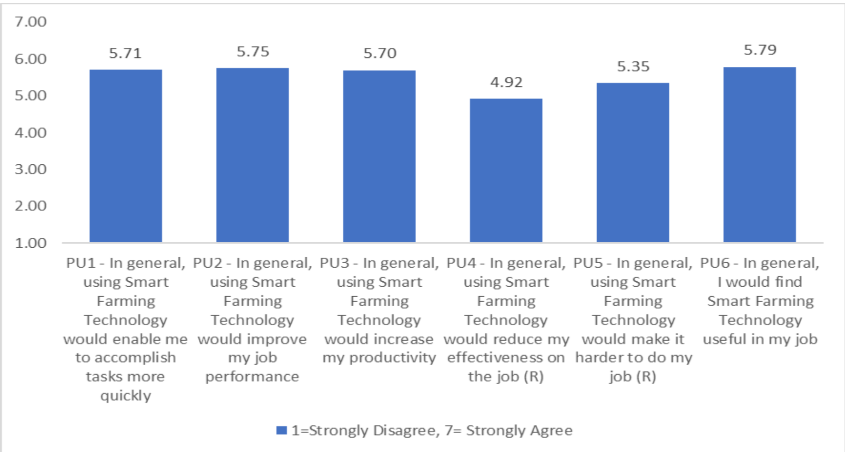

Figure H.3 Perceived Usefulness Average Results

The skewness figures are all within the acceptable range of +/- 2 as shown in Table H.9. Analysis of the kurtosis values indicates a higher value for PU6, suggesting that high number of respondents showed strong agreement with this item. However, the value is still in the acceptable range of +/-7 as outlined by Hair *et al*. (2020) The histogram in Figure H.4 outlines the spread of the value in more detail.

Table H.9 Perceived Usefulness Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PU1	217	3	7	5.71	.965	-.377	.165	-.517	.329
PU2	217	2	7	5.75	1.029	-.644	.165	.099	.329
PU3	217	1	7	5.70	1.066	-.927	.165	1.728	.329
PU4	217	1	7	4.92	1.594	-.507	.165	-.838	.329
PU5	217	1	7	5.35	1.339	-.712	.165	-.052	.329
PU6	217	1	7	5.79	1.059	-1.479	.165	3.950	.329
Valid N (listwise)	217								

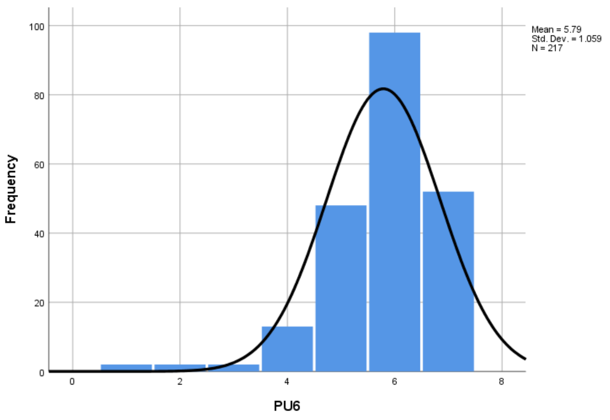

Figure H.4 PU6 Histogram

The Cronbach's Alpha, as outlined in Table H.10 is above the acceptable cut off of 0.70 at 0.769. However, internal consistency of the construct can be improved with the removal of PU4.

Table H.10 Perceived Usefulness Reliability Statistics

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PU1	27.50	18.918	.480	.401	.745
PU2	27.46	17.305	.644	.571	.707
PU3	27.51	17.112	.638	.543	.706
PU4	28.29	16.688	.357	.251	.798
PU5	27.86	16.314	.534	.324	.730
PU6	27.42	17.754	.561	.350	.725

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.769	.794	6

With PU4 removed, the Cronbach's Alpha has improved to .798 as outlined in Table H.11 However, with the removal of PU5, the internal consistency of the construct can be further improved to .826.

Table H.11 Perceived Usefulness Reliability with PU4 removed

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PU1	22.59	11.957	.570	.389	.764
PU2	22.54	10.842	.707	.570	.721
PU3	22.59	10.715	.693	.541	.723
PU5	22.94	11.154	.418	.183	.826
PU6	22.50	11.436	.577	.346	.760

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.798	.810	5

Therefore, item PU4 and PU5 were removed, as outlined in Table H.12.

Table H.12 Perceived Usefulness Reliability with PU4 and PU5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PU1	17.24	7.137	.599	.388	.803
PU2	17.19	6.277	.741	.566	.738
PU3	17.24	6.204	.718	.536	.748
PU6	17.16	6.938	.555	.321	.824

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.826	.826	4

.

Table H.13 below shows that the inter-item correlation between each of the items in the scale is acceptable.

Table H.13 Perceived Usefulness Inter-Item Correlation

Inter-Item Correlation Matrix

	PU1	PU2	PU3	PU6
PU1	1.000	.593	.544	.387
PU2	.593	1.000	.692	.517
PU3	.544	.692	1.000	.522
PU6	.387	.517	.522	1.000

One dimension was obtained, and factor loadings are above the recommended cut-off value of .40 (Hair *et al.*, 1998) as shown in Table H.14.

Table H.14 Perceived Usefulness Reliability and Factor Loadings

	Cronbach's Alpha	**Factor Loadings ****
• In general, using Smart Farming Technology would enable me to accomplish tasks more quickly.	**.826**	.681
• In general, using Smart Farming Technology would improve my job performance.		.830

• In general, using Smart Farming Technology would increase my productivity		.812
• In general, using Smart Farming Technology would reduce my effectiveness on the job (R).*		---
• In general, using Smart Farming Technology would make it harder to do my job (R).*		---
• In general, I would find Smart Farming Technology useful in my job.		.653
***Item deleted to obtain a higher level of reliability. **One dimension determined**		

Following DV tests discussed in Section 5.3, Item 6 was subsequently removed and a Cronbach's Alpha of .824 was achieved, as outlined in Table H.15 below.

Table H.15 Revised Cronbach's Alpha for PU, based on PU1,2,3

Reliability Statistics

Cronbach's Alpha	N of Items
.824	3

H.4 Perceived Ease of Use

Respondents agreed that they perceived SFT as easy to use, as outlined in Figure H.5. PEOU2 and PEOU5 were reverse coded before analysis. Respondents indicated most positively that learning to operate SFT would be easy for them (M = 5.18, ±1.421) and furthermore using SFT would be easy (M = 5.13, ±1.264). The reverse coded item, PEOU2 (I would find it easy to get SFT do what I want it to do), scored the lowest mean at M = 4.30.

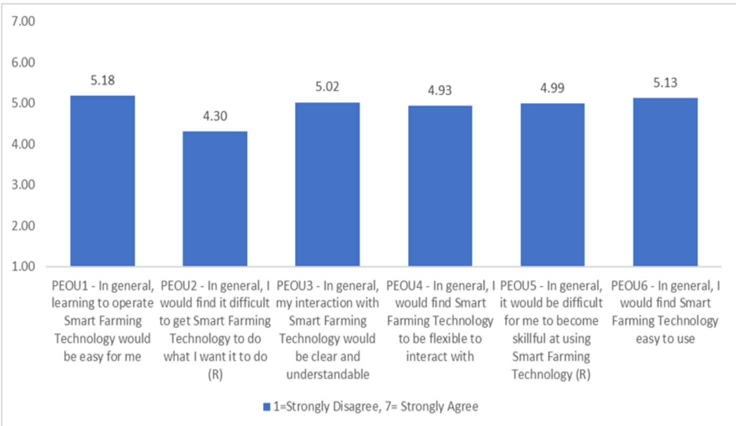

Figure H.5 Perceived Ease of Use Average Results

Results were further assessed based on the farmer's experience of using SFT, as outlined below in Figure H.6.

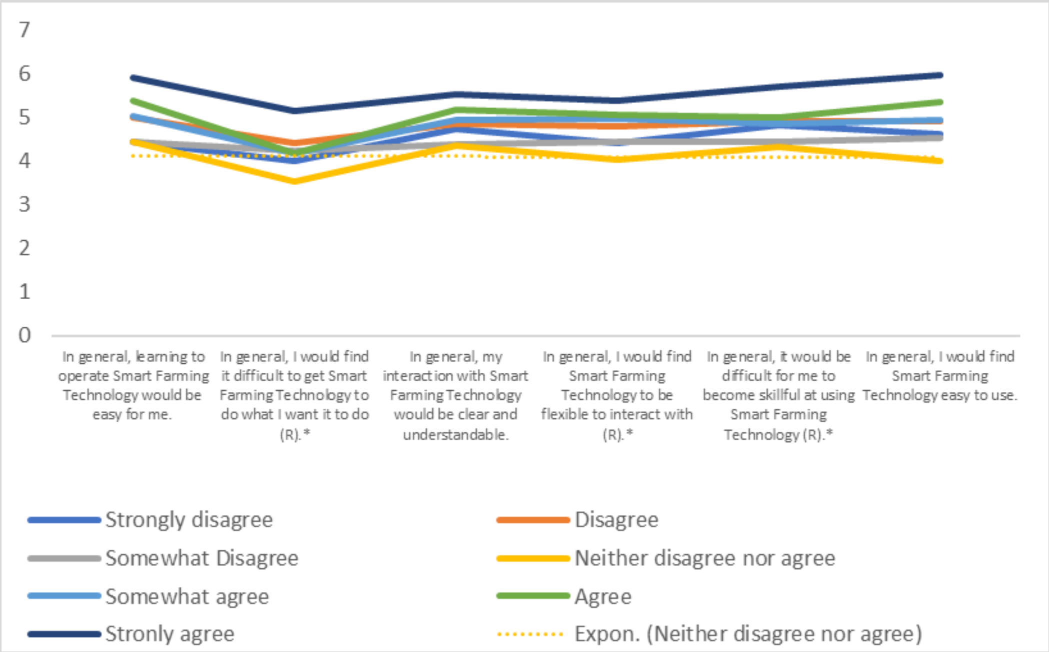

Figure H.6 PEOU item means related to farmers' experience with SFT

Table H.16 shows the descriptive statistics for Perceived Ease of Use. Skewness and Kurtosis figures are all within the acceptable range.

Table H.16 Perceived Ease of Use Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
PEOU1	217	1	7	5.18	1.421	-.859	.165	.077	.329
PEOU2	217	1	7	4.30	1.471	-.019	.165	-.985	.329
PEOU3	217	2	7	5.02	1.128	-.495	.165	.027	.329
PEOU4	217	2	7	4.93	1.180	-.317	.165	-.315	.329
PEOU5	217	1	7	4.99	1.540	-.707	.165	-.491	.329
PEOU6	217	1	7	5.13	1.264	-.796	.165	.232	.329
Valid N (listwise)	217								

The Cronbach's Alpha of Perceived Ease of Use is above the recommended 0.70 at 0.834, and no further improvements can be made.

Table H.17 Reliability Statistics for Perceived Ease of Use

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
PEOU1	24.37	24.059	.674	.576	.793
PEOU2	25.25	25.699	.510	.319	.829
PEOU3	24.53	26.222	.690	.566	.795
PEOU4	24.63	27.818	.503	.413	.827
PEOU5	24.56	24.469	.567	.411	.819
PEOU6	24.42	24.430	.756	.658	.778

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.834	.841	6

Table H.18 outlines the correlations between the items in the Perceived Ease of Use construct and demonstrates strong correlation between items.

Table H.18 Perceived Ease of Use Inter-Item Correlation

Inter-Item Correlation Matrix

	PEOU1	PEOU2	PEOU3	PEOU4	PEOU5	PEOU6
PEOU1	1.000	.375	.598	.353	.485	.724
PEOU2	.375	1.000	.395	.306	.508	.367
PEOU3	.598	.395	1.000	.599	.371	.654
PEOU4	.353	.306	.599	1.000	.237	.522
PEOU5	.485	.508	.371	.237	1.000	.529
PEOU6	.724	.367	.654	.522	.529	1.000

Reliability and factor validity is presented in Table H.19. with all factor loadings >.40 as recommended by Hair *et al.* (1998). PEOU2 is slightly above the threshold.

Table H.19 Final Reliability and Factor Validity for Perceived Ease of Use

	Cronbach's Alpha	**Factor Loadings ****
• In general, learning to operate Smart Farming Technology would be easy for me.	**.834**	.800
• In general, I would find it difficult to get Smart Farming Technology to do what I want it to do (R).*		.486
• In general, my interaction with Smart Farming Technology would be clear and understandable.		.772
• In general, I would find Smart Farming Technology to be flexible to interact with (R).*		.589
• In general, it would be difficult for me to become skillful at using Smart Farming Technology (R).*		.582
• In general, I would find Smart Farming Technology easy to use.		.681
****One dimension determined**		

Following DV tests, as discussed in Section 5.3, items 2, 4 and 5 were subsequently removed. Full details are provided in Appendix I. Cronbach's Alpha was rested and achieved a value of .849.

Table H.20 Cronbach's Alpha on PEOU 1,3,6

Reliability Statistics

Cronbach's Alpha	N of Items
.849	3

H.5 Trust in SFT vendor

As outlined in Figure H.7,trust is a second order factor which combines several first order factors relating to the benevolence, integrity, and competency of the SFT vendor.

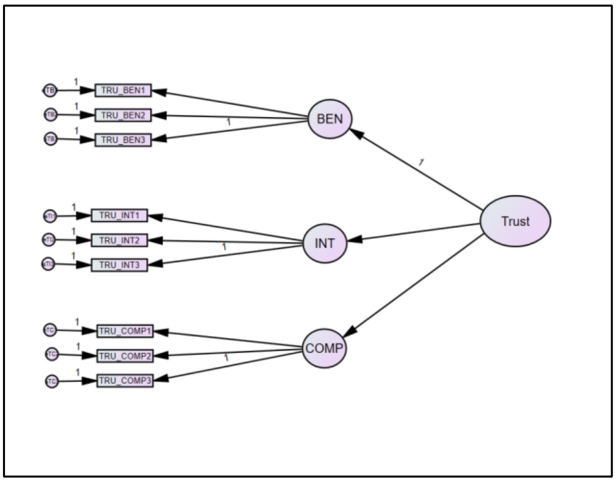

Figure H.7 Trust Variable Structure

The average results for each of the individual elements of the Trust in SFT Vendor are depicted in Figure H.8 Competency scored the highest, followed by Integrity and Benevolence. However, all figures were above 4.00 indicating that respondents agreed with the item statements.

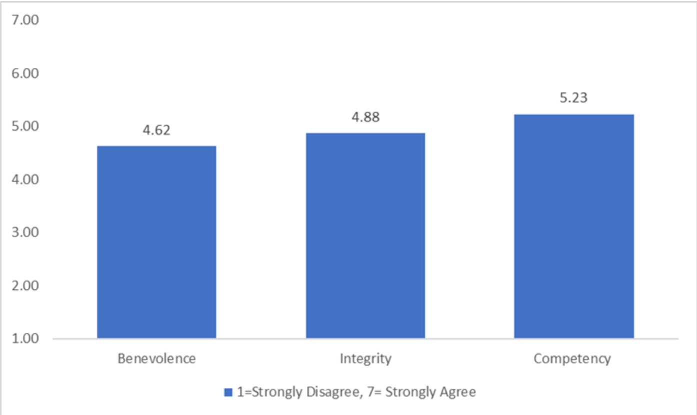

Figure H.8 Trust Average Results

H.5.1 Benevolence

As outlined in Figure H.9, and the descriptive statistics provided in Table H.21, on average, respondents agreed most positively with the statement that SFT vendors would do their best to help farmers if needed (BEN2). The highest mean rating of 5.07 (±1.236) was found for BEN2 while the lowest rating of 4.39 (±1.357) was found for BEN3.

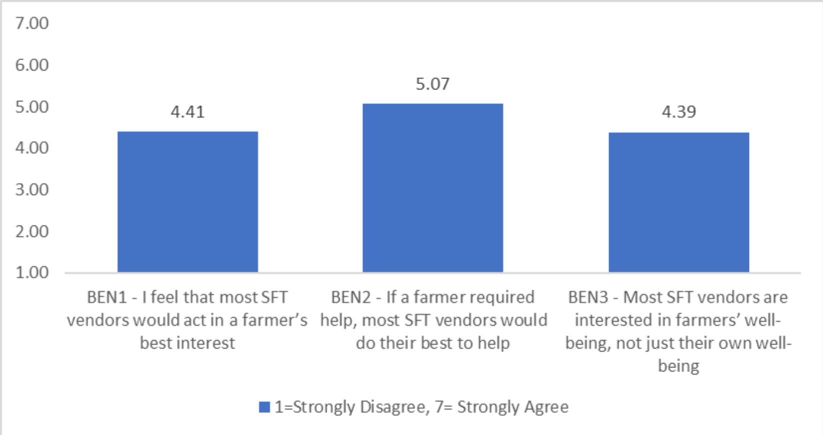

Figure H.9 Trust Benevolence Average Results

All items, as outlined in Table H21, display an acceptable level of kurtosis and skewness.

Table H.21 Trust Benevolence Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
TRU_BEN1	217	1	7	4.41	1.376	-.370	.165	-.522	.329
TRU_BEN2	217	1	7	5.07	1.236	-.964	.165	.869	.329
TRU_BEN3	217	1	7	4.39	1.357	-.292	.165	-.364	.329
Valid N (listwise)	217								

As indicated in Table H.22 below, the obtained Cronbach's Alpha is acceptable (above the recommended cut-off value point of .70) indicating internal reliability of the construct (Hair *et al.*, 2006).

Table H.22 Reliability Statistics for Benevolence

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TRU_BEN1	9.46	5.101	.599	.359	.680
TRU_BEN2	8.80	5.715	.588	.345	.694
TRU_BEN3	9.48	5.158	.603	.364	.674

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.764	.765	3

Table H.23 below shows the correlation between the items in the scale.

Table H.23 Benevolence Inter-Item Correlation

Inter-Item Correlation Matrix

	TRU_BEN1	TRU_BEN2	TRU_BEN3
TRU_BEN1	1.000	.501	.542
TRU_BEN2	.501	1.000	.541
TRU_BEN3	.542	.541	1.000

With regards to factoral validity, outlined in Table H.24 one dimension was obtained and factor loadings are above the recommended cut-off value of .40 (Hair *et al.*, 1998).

Table H.24 Trust in Vendor Benevolence- Factoral Validity Result

	Cronbach's Alpha	**Factor Loadings ****
• I feel that most SFT vendors would act in a farmer's best interest.	**.764**	.679
• If a farmer required help, most SFT vendors would do their best to help.		.726
• Most SFT vendors are interested in farmers' well-being, not just their own well-being.		.753
****One dimension determined**		

H.5.2 Integrity

As outlined in Figure H.10, and the descriptive statistics provided in Table H.25, on average, respondents agreed positively with the statements. The highest mean rating of 5.05 (±1.088) was found for INT3 while the lowest rating of 4.60 (±1.298) was found for INT1 (comfortable relying on SFT vendors to meet their obligations).

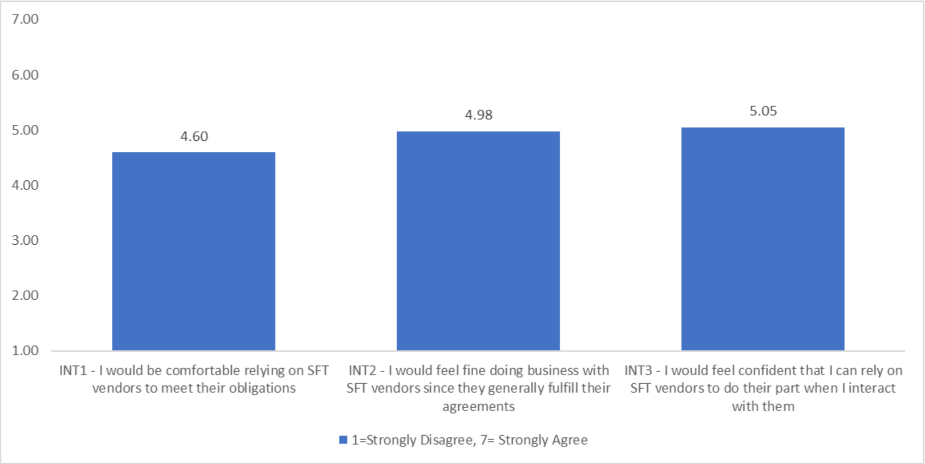

Figure H.10 Trust Integrity Average Results

As outlined in Table H.25, all items display an acceptable level of kurtosis and skewness.

Table H.25 Trust Integrity Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
TRU_INT1	217	1	7	4.60	1.298	-.551	.165	-.042	.329
TRU_INT2	217	1	7	4.98	1.101	-.824	.165	1.050	.329
TRU_INT3	217	1	7	5.05	1.088	-.659	.165	.461	.329
Valid N (listwise)	217								

As indicated in Table H.26, the Cronbach's Alpha achieved is acceptable (above the recommended cut-off value point of .70) indicating internal reliability of the construct (Hair *et al*., 2006). No improvements can be made with deletion of items.

Table H.26 Integrity Reliability Statistics

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TRU_INT1	10.03	3.990	.745	.570	.799
TRU_INT2	9.65	4.645	.776	.603	.765
TRU_INT3	9.59	4.985	.694	.487	.837

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.858	.862	3

Table H.27 shows that there is a strong correlation between each of the items in the construct.

Table H.27 Trust Integrity Inter Item Correlation

Inter-Item Correlation Matrix

	TRU_INT1	TRU_INT2	TRU_INT3
TRU_INT1	1.000	.730	.629
TRU_INT2	.730	1.000	.666
TRU_INT3	.629	.666	1.000

With regards to factoral validity, outlined in Table H.28, one dimension was obtained and factor loadings are above the recommended cut-off value of .40 (Hair *et al.*, 1998).

Table H.28 Trust in Vendor Integrity - Factoral Validity Result

	Cronbach's Alpha	**Factor Loadings ****
• I would be comfortable relying on SFT vendors to meet their obligations	**.858**	.840
• I would feel fine doing business with SFT vendors since they generally fulfil their agreements.		.848
• I would feel confident that I can rely on SFT vendors to do their part when I interact with them.		.783
****One dimension determined**		

H.5.3 Competency

As outlined in Figure H.11, and the descriptive statistics provided in Table H.29, the highest mean rating of 5.29 (±0.930) was found for COMP1 (most SFT vendors are competent in their field) while the lowest rating of 5.18 (±0.964) was found for COMP2 (most SFT vendors do a capable job of meeting farmers' needs).

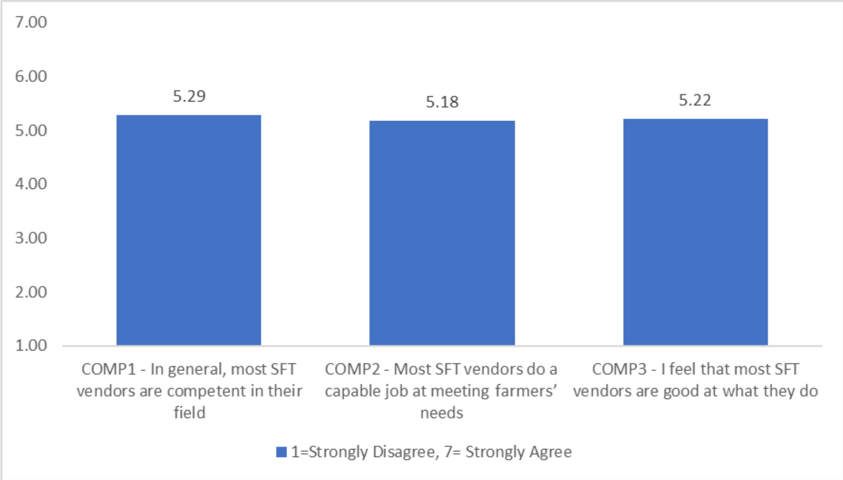

Figure H.11 Trust Competency Average Results

As outlined in Table H.29, all items display an acceptable level of kurtosis and skewness.

Table H.29 Competency Descriptive Statistics

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
TRU_COMP1	217	2	7	5.29	.930	-.645	.165	.231	.329
TRU_COMP2	217	2	7	5.18	.964	-.409	.165	-.148	.329
TRU_CCOMP3	217	1	7	5.22	1.008	-.977	.165	1.749	.329
Valid N (listwise)	217								

The Cronbach's Alpha, as outlined in Table H.30 is strong at .886.

Table H.30 Trust Competency Reliability Results

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
TRU_COMP1	10.41	3.326	.788	.627	.831
TRU_COMP2	10.51	3.195	.794	.636	.823
TRU_CCOMP3	10.47	3.149	.754	.568	.861

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.886	.887	3

As Table H.31 shows, there is a strong correlation between each of the items in the construct.

Table H.31 Trust Competency Inter-Item Correlation

Inter-Item Correlation Matrix

	TRU_COMP1	TRU_COMP2	TRU_CCOMP3
TRU_COMP1	1.000	.756	.702
TRU_COMP2	.756	1.000	.711
TRU_CCOMP3	.702	.711	1.000

The final reliability and factor loadings are outlined in Table H.32, demonstrating unidimensionality and all factor loadings are above the recommended cut-off value of .40 (Hair *et al.*, 1998).

Table H.32 Trust in Vendor Competency - Factoral Validity Result

	Cronbach's Alpha	**Factor Loadings ****
• In general, most SFT vendors are competent in their field.	**.886**	.854
• Most SFT vendors do a capable job at meeting farmers' needs.		.877
• I feel that most SFT vendors are good at what they do.		.821
****One dimension determined**		

H.6 Attitude

Figure H.12 outlines the average results for the construct, attitude. ATT3 was reverse coded before the analysis was conducted. Overall, respondents had a positive attitude towards using SFT. In particular, respondents felt using SFT would be a good idea with a mean of 6.02 (±0.918), followed by respondents liking the idea of using SFT (M = 6.00, ±.940). The respondents also positively agreed with the statements that using SFT would be pleasant and wise.

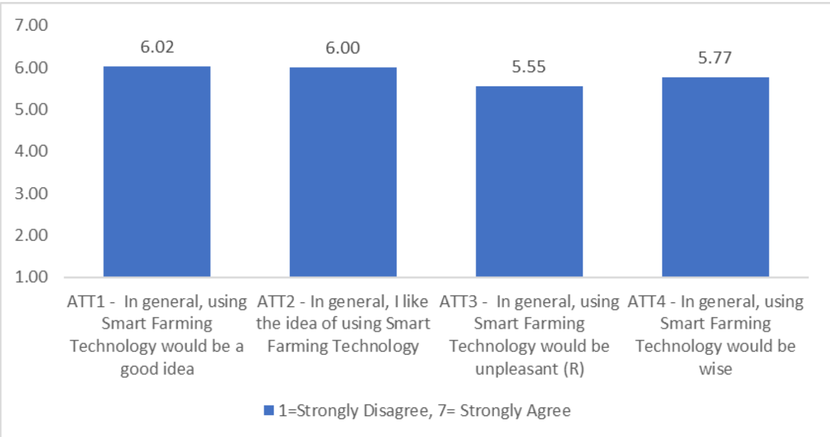

Figure H.12 Attitude Average Results

Analysis of the descriptive statistics in Table H.33 outlines that both skewness and kurtosis are in the acceptable range.

Table H.33 Descriptive Statistics from Attitude

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
ATT1	217	3	7	6.02	.918	-1.088	.165	1.406	.329
ATT2	217	3	7	6.00	.940	-1.122	.165	1.138	.329
ATT3	217	2	7	5.55	1.250	-1.072	.165	.676	.329
ATT4	217	2	7	5.77	.954	-.752	.165	.503	.329
Valid N (listwise)	217								

The inter correlations between items are outlined in Table H.34. The table demonstrates there is a strong correlation between items.

Table H.34 Attitude Inter-Item Correlations

Inter-Item Correlation Matrix

	ATT1	ATT2	ATT3	ATT4
ATT1	1.000	.814	.525	.662
ATT2	.814	1.000	.542	.667
ATT3	.525	.542	1.000	.457
ATT4	.662	.667	.457	1.000

The Cronbach's Alpha for attitude is above the recommended value of 0.70 at .845. However, with the removal of ATT3, it can be improved to .881.

Table H.35 Reliability Statistics for Attitude

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ATT1	17.32	6.923	.768	.663	.773
ATT2	17.34	6.724	.793	.689	.760
ATT3	17.79	6.387	.558	.318	.881
ATT4	17.57	7.116	.678	.508	.807

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.845	.861	4

With ATT3, the reliability statistics indicate that the Cronbach's Alpha can be further improved with the removal of ATT4 as demonstrated in Table H.36 and H.37.

Table H.36 Reliability Statistics for Attitude with ATT3 removed

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ATT1	11.77	3.018	.792	.657	.811
ATT2	11.79	2.909	.809	.675	.795
ATT4	12.02	3.097	.709	.504	.885

Table H.37 Reliability Statistics for Attitude with ATT3 and ATT4 removed

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ATT1	6.00	.884	.794	.630	.
ATT2	6.02	.842	.794	.630	.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.885	.885	2

The final reliability and factor loadings are outlined in Table H.38 demonstrating unidimensionality and all factor loadings are above the recommended cut-off value of .40 (Hair *et al.*, 1998).

Table H.38 Reliability and Factor Loadings for Attitude

	Cronbach's Alpha	**Factor Loadings ****
• In general, using Smart Farming Technology would be a good idea.	**.885**	.850
• In general, I like the idea of using Smart Farming Technology.		.934
• In general, using Smart Farming Technology would be unpleasant (R)*		---
• In general, using Smart Farming Technology would be wise.*		---
***Item deleted to obtain a higher level of reliability **One dimension determined**		

H.7 Behavioural Intention

Respondents were positively disposed to intending to adopt SFT. As illustrated in Figure H.13, they agreed that assuming they had access to SFT, they predict they would use it (M = 6.10, ±1.103).

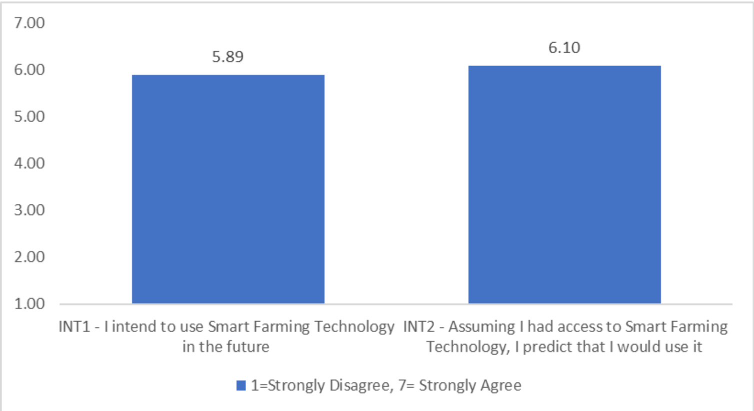

Figure H.13 Behavioural Intention to adopt SFT Average Results

The descriptive statistics in Table H.39 indicates that there is a negatively skewed distribution, but it is still in the acceptable range of -/+2. However, Kurtosis is >3 indicating a leptokurtic distribution, containing more extreme values. It is still in the acceptable range of +/-7 (Hair *et al*., 2010). The histograms in Figure H.14 outlines the spread of the value for each of the items in more detail.

Table H.39 Descriptive Statistics for Behavioural Intention to adopt

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
INTENT 1	217	1	7	5.89	1.103	-1.525	.165	4.000	.329
INTENT 2	217	1	7	6.10	.981	-1.602	.165	4.141	.329
Valid N (listwise)	217								

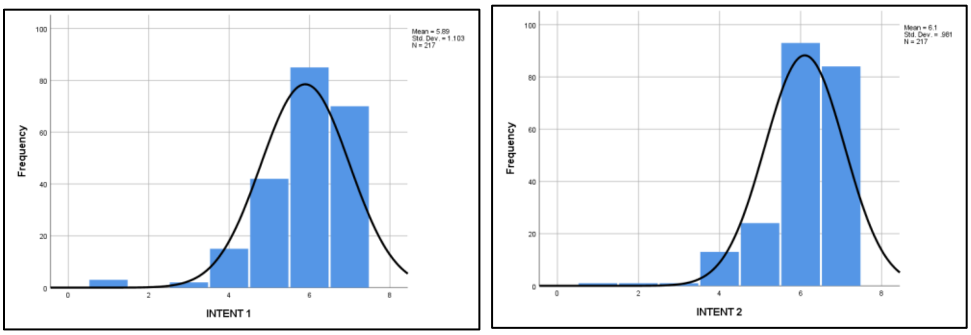

Figure H.14 Histogram for Behavioural Intention 1 and Behavioural Intention 2

Figures from the Inter-Item Correlation Matrix as outlined in Table H.40 are below the cut-off point of 0.90, as recommended.

Table H.40 Inter-Item Correlation Matrix for Intention to adopt

Inter-Item Correlation Matrix

	INTENT 1	INTENT 2
INTENT 1	1.000	.571
INTENT 2	.571	1.000

The Cronbach's Alpha for Behavioural Intention to adopt is above the recommended threshold of 0.70 and thus deemed acceptable.

Table H.41 Reliability Statistics for Behavioural Intention to adopt

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
INTENT 1	6.10	.962	.571	.326	.
INTENT 2	5.89	1.216	.571	.326	.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.724	.727	2

All factor loadings are above the recommended cut-off value of .40 (Hair *et al.*, 1998) outlined in Table H.42 and one dimension was achieved.

Table H.42 Reliability and Factor Loading for Behavioural Intention to adopt

	Cronbach's Alpha	**Factor Loadings ****
• I intend to use Smart Farming Technology in the future	**.724**	.856
• Assuming I had access to Smart Farming Technology, I predict that I would use it.		.667
****One dimension determined**		

Table H.43 outlines the final factor loadings for all constructs

Table H.43 Factor loadings for all item constructs

			Estimate
SINF2_importanttome	<---	SI	.863
SINF1_influencebehaviour	<---	SI	.809
PU3increase_productivity	<---	PU	.812
PU2improve_job_performance	<---	PU	.830
PU1accomplish_tasks_quickly	<---	PU	.681
PEOU6easy_to_use	<---	PEOU	.867
PEOU3interaction_clear	<---	PEOU	.772
PEOU1easytolearn	<---	PEOU	.800
ATT1good_idea	<---	ATT	.850
ATT2like_idea	<---	ATT	.934
PIIT4_experiment	<---	PIIT	.820
PIIT3_hestitant	<---	PIIT	.701
PIIT2_first_to_try	<---	PIIT	.746
PIIT1_experiment_newtech	<---	PIIT	.718
INTENT2_predict_use	<---	INTENT	.856

			Estimate
INTENT1_adoptinfuture	<---	INTENT	.667
TRU_BEN3_farmers_wellbeing	<---	TRU_BEN	.753
TRU_BEN2_helpfarmers	<---	TRU_BEN	.726
TRU_BEN1_bestinterests	<---	TRU_BEN	.679
TRU_INT3_dotheirpart	<---	TRU_INT	.783
TRU_INT2_fulfiill_agreements	<---	TRU_INT	.848
TRU_INT1_meet_obligations	<---	TRU_INT	.840
TRU_CCOMP3_goodatwhattheydo	<---	TRU_COM	.821
TRU_COMP2_meetneeds	<---	TRU_COM	.877
TRU_COMP1_competent	<---	TRU_COM	.854

Appendix I Validity Testing

I.1 Validity Testing for PEOU

As discussed in Section 5.3.2 and illustrated in Table I.1, the Average Variance Extracted (AVE) for PEOU is <.50 threshold as recommended by Hair *et al.* (2019a).

Table I.1 AVE results for each factor

	CR	AVE
TRU_INT	0.864	0.679
SI	0.654	0.654
PU	0.834	0.560
PEOU	0.844	0.485
ATT	0.887	0.797
PIIT	0.835	0.559
INTENT	0.738	0.589
TRU_BEN	0.763	0.518
TRU_COM	0.887	0.724

The factor loadings for PEOU, as outlined in Appendix H, were consulted. PEOU2 showed the lowest factor loading of .486 and was marked as a candidate for removal. However, an AVE >.50 was not achieved therefore Item 4 (factor loading .582) and Item 5 (factor loading .589) were subsequently removed, and a strong AVE of .664 was achieved, as outlined in Table I.2.

Table I.2 Final AVE scores for each factor

	CR	AVE
TRU_INT	0.864	0.679
SI	0.654	0.654
PU	0.834	0.559
PEOU	0.855	0.664
ATT	0.888	0.798
PIIT	0.834	0.559
INTENT	0.738	0.588
TRU_BEN	0.763	0.518
TRU_COM	0.888	0.725

I.2 Validity Testing for Second Order Factor (Trust)

The Pearson Correlation between Benevolence and Integrity is relatively strong 0.720 at a highly significant level of < .000 as indicated in Table I.3 . Equally, the correlation coefficient between Integrity and Competency is 0.681 and again with significance level of < .01. The figure of .570 indicates there is positive correlation between Competency and Benevolence, with a significance level of < .01.

Table I.3 Correlations between Trust factors

Correlations

		All_Tru_ben	All_Tru_int	All_Tru_comp
All_Tru_ben	Pearson Correlation	1	.720**	.570**
	Sig. (2-tailed)		.000	.000
	N	217	217	217
All_Tru_int	Pearson Correlation	.720**	1	.681**
	Sig. (2-tailed)	.000		.000
	N	217	217	217
All_Tru_comp	Pearson Correlation	.570**	.681**	1
	Sig. (2-tailed)	.000	.000	
	N	217	217	217

**. Correlation is significant at the 0.01 level (2-tailed).

Table I.4 confirms there are no issues with correlations among the first order factors in Trust.

Table I.4 Trust Convergent and Discriminant Validity Test Output

Correlations			Estimate
Benevolence	<-->	Integrity	0.893
Benevolence	<-->	Competency	0.684
Integrity	<-->	Competency	0.765

Standardized Regression Weights			Estimate
TRU_BEN3_farmers_wellbeing	<---	Benevolence	0.743
TRU_BEN2_helpfarmers	<---	Benevolence	0.729
TRU_BEN1_bestinterests	<---	Benevolence	0.688
TRU_INT3_dotheirpart	<---	Integrity	0.781
TRU_INT2_fulfiill_agreements	<---	Integrity	0.846
TRU_INT1_meet_obligations	<---	Integrity	0.844
TRU_CCOMP3_goodatwhattheydo	<---	Competency	0.822
TRU_COMP2_meetneeds	<---	Competency	0.879
TRU_COMP1_competent	<---	Competency	0.851

On analysis of the three first order factors in Trust, there is an issue with discriminant validity for Benevolence, as outlined Table I.5. The square root of the AVE for BEN is less than the absolute value of its correlation with INTG. There is also a discriminant validity issue for Integrity: the square root of the AVE for COMP is less than the absolute value of its correlation with BEN.

Table I.5 Trust Validity Results

	CR	AVE	MSV	MaxR(H)	BEN	INTG	COMP
BEN	0.764	0.519	0.797	0.766	**0.720**		
INTG	0.864	0.679	0.797	0.868	0.893***	**0.824**	
COMP	0.887	0.724	0.585	0.890	0.684***	0.765***	**0.851**

Significance of Correlations: * p < 0.050 ** p < 0.010 *** p < 0.001

BEN1 was removed firstly as this had the lowest factor loading. As outlined in Table I.6, this resulted in an issue with composite reliability being <.80. As there were only two items remaining, CR could not be improved, as only having one indicator would not make the variable latent.

Table I.6 Trust Validity Results with BEN1 removed

	CR	AVE	MSV	MaxR(H)	BEN	INTG	COMP
BEN	0.682	0.517	0.864	0.682	**0.719**		
INTG	0.864	0.679	0.864	0.869	0.929***	**0.824**	
COMP	0.887	0.724	0.580	0.890	0.685***	0.762***	**0.851**

Significance of Correlations: * $p < 0.050$ ** $p < 0.010$ *** $p < 0.001$

As a result, Benevolence was removed and DV results were conducted again. This time, there were no validity concerns., as outlined in Table I.7.

Table I.7 Trust Validity Results with BEN removed

	CR	AVE	MSV	MaxR(H)	INTG	COMP
INTG	0.861	0.675	0.622	0.863	**0.821**	
COMP	0.887	0.724	0.622	0.891	0.789***	**0.851**

Appendix J Modification Indices Testing

Table J.1 Covariances: (Group number 1 - Default model)

			M.I.	Par Change
eTI1	<-->	INTENT	6.733	-.106
eTI1	<-->	PIIT	4.882	.114
eTI1	<-->	eTCo1	5.189	-.082
eTI1	<-->	eTIn1	5.049	.089
eTI2	<-->	eTI1	12.002	.138
eTI3	<-->	PIIT	12.618	-.147
eTI3	<-->	eTCo1	15.822	.115
eTI3	<-->	eTIn1	10.443	-.102
eI1	<-->	eTI1	4.392	-.111
eP1	<-->	eTI2	5.816	.093
eP2	<-->	eP1	4.207	.118
eA1	<-->	PEOU	4.389	.071
ePE1	<-->	PU	5.581	-.075
ePE1	<-->	eP4	4.631	.114
ePE3	<-->	ATT	7.759	-.081
ePE3	<-->	PU	10.667	.091
ePE3	<-->	SI	5.715	.162
ePE6	<-->	eA1	7.366	.080
ePU1	<-->	eTCo1	4.020	.062
ePU1	<-->	eTC2	4.128	.057
ePU2	<-->	eI1	5.098	.090
ePU2	<-->	eI2	4.135	-.061
ePU2	<-->	ePE3	4.681	.079
ePU3	<-->	eTCo1	4.371	-.062
ePU3	<-->	eTIn1	8.889	.100
ePU3	<-->	eTI3	4.444	.072
eS1	<-->	eTI1	4.004	-.126
eS2	<-->	ePE3	7.710	.149

Table J.2 Standardized Residual Covariances (Group number 1 - Default model)

	TRU_COMP1	TRU_COMP2	TRU_CCOMP3	TRU_INT1	TRU_INT2_	TRU_INT3_	INTENT1_	INTENT2	PIIT1	PIIT2_	PIIT3_	PIIT4_	ATT2	ATT1	PEOU1	PEOU3	PEOU6	PU1	PU2	PU3	SINF1_	SINF2
TRU_COMP1	0																					
TRU_COMP2	0.057	0																				
TRU_CCOMP3	0.042	-0.107	0																			
TRU_INT1	-0.413	-0.002	-0.142	0																		
TRU_INT2_	-0.258	0.064	0.591	0	0																	
TRU_INT3_	-0.203	0.109	0.096	0.114	-0.066	0																
INTENT1_	1.277	-0.206	0.46	-1.619	0.518	0.001	0															
INTENT2	0.357	0.11	-0.75	-1.441	0.174	-0.086	0	0														
PIIT1	0.638	0.611	0.569	0.566	2.186	-0.249	0.173	1.026	0													
PIIT2_	0.239	0.212	-0.637	0.885	1.072	-0.931	-1.06	-0.749	0	0												
PIIT3_	0.321	-0.098	-0.443	0.046	0.499	-0.551	0.154	0.331	-0.175	-0.013	0											
PIIT4_	0.501	0.167	-0.079	0.407	0.839	-1.195	-0.86	0.189	0.004	0.267	-0.173	0										
ATT2	0.49	-0.092	-0.246	-1.2	0.483	-0.23	0.247	0.075	0.661	-0.882	0.166	0.265	0									
ATT1	0.075	0.29	0.164	-0.684	0.768	-0.225	-0.058	-0.427	0.044	-0.503	-0.121	-0.309	0	0								
PEOU1	-0.355	-0.786	-1.131	-1.242	-0.284	-0.88	-0.038	0.118	-0.248	0.404	0.94	0.699	-0.042	0.311	0							
PEOU3	1.311	0.538	0.978	1.198	1.03	1.089	-0.199	0.091	-0.387	0.467	0.14	-0.437	-0.357	0.175	-0.313	0						
PEOU6	0.332	-0.552	0.431	0.339	1.018	0.229	-0.499	0.065	-0.446	-0.482	0.235	-0.631	-0.248	0.969	0.067	0.145	0					
PU1	0.293	0.792	0.534	-0.834	-0.535	-0.262	-0.303	0.385	0.613	-0.949	0.023	-0.004	0.104	0.545	-0.972	0.328	-0.506	0				
PU2	0.199	-0.644	0.061	-0.574	-0.239	-0.801	0.944	-0.419	1.427	-0.381	0.125	0.102	-0.215	0.009	-0.275	1.744	0.304	0.091	0			
PU3	0.008	-0.046	-0.159	0.007	1.173	1.07	0.097	-0.05	0.525	-1.166	-0.332	-0.031	0.029	0.208	-1.078	1.051	-0.161	-0.269	0.069	0		
SINF1_	-0.332	-0.833	-0.703	-1.176	-0.301	-0.18	-0.077	-0.609	-0.098	-0.529	-0.402	-0.931	-1.009	-0.667	-0.853	0.044	-1.387	-0.851	-0.928	-0.837	-0.525	
SINF2	0.856	-0.019	-0.001	0.772	1.023	0.303	-0.165	0.487	0.879	0.718	0.336	0.154	0.625	0.616	0.025	2.227	0.257	0.343	0.599	0.734	-0.119	0.382

Appendix K Measurement SEM Model 6 Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	58	219.006	173	.010	1.266
Saturated model	231	.000	0		
Independence model	21	2499.142	210	.000	11.901

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	.912	.894	.980	.976	.980
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	.824	.752	.807
Saturated model	.000	.000	.000
Independence model	1.000	.000	.000

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	.035	.018	.049	.967
Independence model	.225	.217	.233	.000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	335.006	348.161	531.040	589.040
Saturated model	462.000	514.392	1242.756	1473.756
Independence model	2541.142	2545.905	2612.120	2633.120

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	1.551	1.394	1.745	1.612
Saturated model	2.139	2.139	2.139	2.381
Independence model	11.765	11.036	12.527	11.787

Appendix L Chi-Square Difference Testing

Table L.1 Chi-square difference testing

Model Testing	$\Delta\chi2$	Δdf	Official Critical Value	Interpretation
SEM Model 2-1	121.473	2	5.991	There is a significant difference between Nested Model and Baseline Model.
SEM Model 3-1	52.995	3	7.815	There is a significant difference between Nested Model and Baseline Model.
SEM Model 4-1	19.965	2	5.991	There is a significant difference between Nested Model and Baseline Model.

Appendix M Mediation Testing

Personal Innovativeness in IT Domain – Perceived Usefulness, mediated by Perceived Ease of Use.

First, PIIT was positively associated with PU (β = .3084, t (215) = 6.1282, p = .000). It was also found that PIIT had a positive relationship with PEOU (β = .5900, t (215) = 10.4103, p = .000). Similarly, the results indicated that the mediator, PEOU, was positively associated with PU (β = .2114, t (215) = 3.5863, p = .0004). As both the a-path and b-path were significant, mediation analyses were tested using the using the bootstrapping method with bias-corrected confidence estimates (MacKinnon *et al.*, 2004; Preacher *et al.*, 2007). The 95% confidence interval of the indirect effects was obtained with 5,000 bootstrap samples as recommended by (Preacher and Hayes, 2008). Results of the mediation analysis confirmed the mediating role of PEOU in the relationship between PIIT and PU (β=.1247 CI=0.1404 to 0.2108). Furthermore, the results indicated that the direct effect of PIIT on PU remained significant (β=.1836, t(215)=3.0567, p=.0025) when controlling for PEOU, thus suggesting a complimentary partial mediation.

Personal Innovativeness in IT Domain – Behavioural Intention, mediated by Perceived Usefulness.

PIIT was positively associated with BI (β = .4080, t (215) = 8.1320, p = .000). Similarly, it was found that PIIT had a positive relationship with PU (β = .3084, t (215) = 6.1282, p = .000). In line with this, the results indicated that the mediator, PU, was positively associated with BI (β = .4698, t (215) = 7.8157, p = .0000). As both the a-path and b-path were significant, mediation analyses were tested using the using the bootstrapping method with bias-corrected confidence estimates (MacKinnon *et al.*, 2004; Preacher *et al.*, 2007). Results of the mediation analysis confirmed the mediating role of PU in the relationship between PIIT and BI (β=.1449 CI=0.0876 to 0.2106). Furthermore, the results indicated that the direct effect of PIIT on BI remained significant (β=.2631, t(215)=5.4731, p=.0000) when controlling for PU, thus suggesting a complimentary partial mediation.

Perceived Ease of Use – PU, mediated by Trust

To begin with, PEOU was positively associated with PU (β = .3157, t (215) = 6.4446, p = .000). Additionally, PEOU had a positive relationship with trust (β = .1664, t (215) = 3.2017, p = .0016). In alignment with these findings, the results indicated that the mediator, trust, was positively associated with PU (β = .2639, t (215) = 4.2663, p = .0000).

As both the a-path and b-path were significant, mediation analyses were tested using the using the bootstrapping method with bias-corrected confidence estimates (MacKinnon *et al.*, 2004; Preacher *et al.*, 2007). Results of the mediation analysis confirmed the mediating role of trust in the relationship between PEOU and PU (β=.0439 CI=0.0119 to 0.0905). Furthermore, the results indicated that the direct effect of PEOU on PU remained significant (β=.2718, t(215)=5.6332, p=.0000) when controlling for trust, thus suggesting a complimentary partial mediation.

Perceived Ease of Use – Attitude, mediated by Trust

Initially, PEOU was positively associated with ATT (β = .3258, t (215) = 7.0391, p = .000). Concurrently, it was established that PEOU had a positive relationship with trust (β = .1664, t (215) = 3.2017, p = .0016). Similarly, the results indicated that the mediator, trust, was positively associated with ATT (β = .2914, t (215) = 5.0649, p = .0000). Given that both the a-path and b-path were significant, mediation analyses were tested using the using the bootstrapping method with bias-corrected confidence estimates (MacKinnon *et al.*, 2004; Preacher *et al.*, 2007). Results of the mediation analysis confirmed the mediating role of trust in the relationship between PEOU and ATT (β=.0485 CI=0.0123 to 0.0973). Furthermore, the results indicated that the direct effect of PEOU on ATT remained significant (β=.2773, t(215)=6.1801, p=.0000) when controlling for Trust, thus suggesting a complimentary partial mediation.

Trust - Attitude, mediated by Perceived Usefulness

First, a positive correlation between trust and ATT was established (β = .3672, t (215) = 6.0327, p = .000). It was also found that trust had a positive relationship with PU (β = .3383, t (215) = 5.2352, p = .000). Similarly, the results indicated that PU, serving as the mediator, was positively associated with ATT (β = .6019, t (215) = 12.1480, p = .000). As both the a-path and b-path were significant, mediation analyses were tested using the using the bootstrapping method with bias-corrected confidence estimates (MacKinnon *et al.*, 2004; Preacher *et al.*, 2007). Results of the mediation analysis confirmed the mediating role of PU in the relationship between trust and attitude (β=.0485, CI=0.1148 to 0.2996). Furthermore, the results indicated that the direct effect of trust on ATT remained significant (β=.1636, t(215)=3.2830, p=.0012 when controlling for PU, thus suggesting a complimentary partial mediation.

Perceived Usefulness – Behavioural Intention, mediated by Attitude

First, PU was positively associated with BI (β = .5967, t (215) = 10.0996, p = .000). It was also found that PU had a positive relationship with ATT (β = .6566, t (215) = 13.7618, p = .000). Similarly, the results indicated that the mediator, ATT, was positively associated with BI (β = .3831, t (215) = 4.7597, p = .000). As both the a-path and b-path were significant, mediation analyses were tested using the using the bootstrapping method with bias-corrected confidence estimates (MacKinnon *et al.*, 2004; Preacher *et al.*, 2007). Results of the mediation analysis confirmed the mediating role of ATT in the relationship between PEOU and BI (β=.2516, CI=0.1404 to 0.3686). Furthermore, the results indicated that the direct effect of PEOU on Intent remained significant (β=.3451, t(215)=4.789, p=.0000) when controlling for ATT, thus suggesting a complimentary partial mediation.

Appendix N Moderation Testing

N.1 PU – BI, moderated by Age

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.570[a]	.325	.319	.76210	.325	51.619	2	214	.000
2	.586[b]	.343	.334	.75383	.018	5.717	1	213	.018

a. Predictors: (Constant), Age, PU_fin

b. Predictors: (Constant), Age, PU_fin, PUAGE

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	59.960	2	29.980	51.619	.000[b]
	Residual	124.289	214	.581		
	Total	184.249	216			
2	Regression	63.209	3	21.070	37.077	.000[c]
	Residual	121.040	213	.568		
	Total	184.249	216			

a. Dependent Variable: INT_fin

b. Predictors: (Constant), Age, PU_fin

c. Predictors: (Constant), Age, PU_fin, PUAGE

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.674	.351		7.608	.000
	PU_fin	.597	.059	.568	10.110	.000
	Age	-.038	.035	-.060	-1.077	.283
2	(Constant)	2.627	.348		7.545	.000
	PU_fin	.602	.058	.573	10.303	.000
	Age	-.031	.035	-.050	-.892	.373
	PUAGE	.125	.052	.133	2.391	.018

a. Dependent Variable: INT_fin

N.2 PU – BI, moderated by Gender

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.578[a]	.334	.328	.75737	.334	53.606	2	214	.000
2	.578[b]	.334	.324	.75914	.000	.001	1	213	.973

a. Predictors: (Constant), Gender, PU_fin

b. Predictors: (Constant), Gender, PU_fin, PUGEN

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	61.497	2	30.749	53.606	.000[b]
	Residual	122.752	214	.574		
	Total	184.249	216			
2	Regression	61.498	3	20.499	35.571	.000[c]
	Residual	122.751	213	.576		
	Total	184.249	216			

a. Dependent Variable: INT_fin

b. Predictors: (Constant), Gender, PU_fin

c. Predictors: (Constant), Gender, PU_fin, PUGEN

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.237	.383		5.838	.000
	PU_fin	.593	.059	.564	10.108	.000
	Gender	.204	.104	.110	1.963	.051
2	(Constant)	2.271	1.076		2.110	.036
	PU_fin	.587	.196	.558	2.990	.003
	Gender	.185	.565	.100	.328	.743
	PUGEN	.003	.103	.012	.034	.973

a. Dependent Variable: INT_fin

N.3 PU – BI, moderated by Education

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.571[a]	.326	.319	.76190	.326	51.702	2	214	.000
2	.573[b]	.329	.319	.76204	.003	.922	1	213	.338

a. Predictors: (Constant), Educat, PU_fin

b. Predictors: (Constant), Educat, PU_fin, PUEDU

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	60.025	2	30.012	51.702	.000[b]
	Residual	124.224	214	.580		
	Total	184.249	216			
2	Regression	60.560	3	20.187	34.763	.000[c]
	Residual	123.689	213	.581		
	Total	184.249	216			

a. Dependent Variable: INT_fin

b. Predictors: (Constant), Educat, PU_fin

c. Predictors: (Constant), Educat, PU_fin, PUEDU

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	2.441	.365		6.691	.000
	PU_fin	.598	.059	.569	10.127	.000
	Educat	.040	.035	.063	1.128	.261
2	(Constant)	3.184	.856		3.721	.000
	PU_fin	.468	.148	.445	3.172	.002
	Educat	-.184	.236	-.293	-.780	.436
	PUEDU	.039	.041	.378	.960	.338

a. Dependent Variable: INT_fin

N.4 PU – BI, moderated by Farm Size

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.569[a]	.323	.317	.76333	.323	51.105	2	214	.000
2	.598[b]	.357	.348	.74574	.034	11.216	1	213	.001

a. Predictors: (Constant), What is the size of your farm, in hectares?, PU_fin

b. Predictors: (Constant), What is the size of your farm, in hectares?, PU_fin, PUFSZE

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	59.556	2	29.778	51.105	.000[b]
	Residual	124.693	214	.583		
	Total	184.249	216			
2	Regression	65.793	3	21.931	39.435	.000[c]
	Residual	118.456	213	.556		
	Total	184.249	216			

a. Dependent Variable: INT_fin

b. Predictors: (Constant), What is the size of your farm, in hectares?, PU_fin

c. Predictors: (Constant), What is the size of your farm, in hectares?, PU_fin, PUFSZE

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.488	.371		6.709	.000
	PU_fin	.592	.060	.563	9.953	.000
	What is the size of your farm, in hectares?	.026	.038	.038	.680	.497
2	(Constant)	-1.244	1.172		-1.061	.290
	PU_fin	1.265	.209	1.203	6.049	.000
	What is the size of your farm, in hectares?	.837	.245	1.244	3.416	.001
	PUFSZE	-.145	.043	-1.436	-3.349	.001

a. Dependent Variable: INT_fin

Appendix O Hypotheses Testing

Regression Weights								Standardized Regression Weights			
			Estimate	S.E.	C.R.	P	Label				Estimate
PEOU	<---	PIIT	0.722	0.08	8.999	***	par_18	PEOU	<---	PIIT	0.699
PU	<---	PIIT	0.268	0.094	2.843	0.004	par_17	PU	<---	PIIT	0.33
PU	<---	SI	0.101	0.046	2.202	0.028	par_20	PU	<---	SI	0.18
PU	<---	PEOU	0.157	0.087	1.803	0.071	par_21	PU	<---	PEOU	0.2
Trust	<---	PEOU	0.043	0.067	0.647	0.518	par_23	Trust	<---	PEOU	0.056
Trust	<---	PU	0.378	0.098	3.87	***	par_28	Trust	<---	PU	0.382
Intention	<---	PIIT	0.281	0.089	3.174	0.002	par_19	Intention	<---	PIIT	0.371
Intention	<---	PU	0.454	0.078	5.815	***	par_22	Intention	<---	PU	0.486
Intention	<---	PEOU	-0.007	0.075	-0.096	0.924	par_29	Intention	<---	PEOU	-0.01
Intg	<---	Trust	1					Intg	<---	Trust	0.872
Comp	<---	Trust	0.925	0.153	6.046	***	par_14	Comp	<---	Trust	0.953
PIIT4_experiment	<---	PIIT	1					PIIT4_experiment	<---	PIIT	0.827
PIIT3_hestitant	<---	PIIT	1.064	0.1	10.63	***	par_1	PIIT3_hestitant	<---	PIIT	0.711
PIIT2_first_to_try	<---	PIIT	0.979	0.094	10.466	***	par_2	PIIT2_first_to_try	<---	PIIT	0.711
PIIT1_experiment_newtech	<---	PIIT	0.69	0.07	9.883	***	par_3	PIIT1_experiment_newtech	<---	PIIT	0.678
SINF2_importanttome	<---	SI	1					SINF2_importanttome	<---	SI	0.978
SINF1_influencebehaviour	<---	SI	0.612	0.167	3.663	***	par_4	SINF1_influencebehaviour	<---	SI	0.644
PU3increase_productivity	<---	PU	1					PU3increase_productivity	<---	PU	0.805
PU2improve_job_performance	<---	PU	1.026	0.083	12.408	***	par_5	PU2improve_job_performance	<---	PU	0.856
PU1accomplish_tasks_quickly	<---	PU	0.772	0.076	10.123	***	par_6	PU1accomplish_tasks_quickly	<---	PU	0.686
PEOU6easy_to_use	<---	PEOU	1					PEOU6easy_to_use	<---	PEOU	0.862
PEOU3interaction_clear	<---	PEOU	0.769	0.064	11.943	***	par_7	PEOU3interaction_clear	<---	PEOU	0.743
PEOU1easytolearn	<---	PEOU	1.09	0.08	13.636	***	par_8	PEOU1easytolearn	<---	PEOU	0.836
TRU_INT3_dotheirpart	<---	Intg	1					TRU_INT3_dotheirpart	<---	Intg	0.895
TRU_INT2_fulfiill_agreements	<---	Intg	0.847	0.073	11.591	***	par_9	TRU_INT2_fulfiill_agreements	<---	Intg	0.749
TRU_INT1_meet_obligations	<---	Intg	0.925	0.088	10.513	***	par_10	TRU_INT1_meet_obligations	<---	Intg	0.694
TRU_CCOMP3_goodatwhattheydo	<---	Comp	1					TRU_CCOMP3_goodatwhattheydo	<---	Comp	0.818
TRU_COMP2_meetneeds	<---	Comp	1.029	0.069	14.933	***	par_11	TRU_COMP2_meetneeds	<---	Comp	0.88
TRU_COMP1_competent	<---	Comp	0.962	0.067	14.397	***	par_12	TRU_COMP1_competent	<---	Comp	0.853
INTENT2_predict_use	<---	Intention	1					INTENT2_predict_use	<---	Intention	0.82
INTENT1_adoptinfuture	<---	Intention	0.946	0.104	9.111	***	par_13	INTENT1_adoptinfuture	<---	Intention	0.689