Farmers’ use of mobile phone applications in Abia state, Nigeria

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Abstract of a thesis submitted in partial fulfilment of the requirements for the Degree of Master of Commerce (Agricultural).

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In developing countries such as Nigeria, agriculture is the main source of livelihood where over 70 percent of the population engage in farming. They are mostly smallholders who are often subsistence farmers with minimal use of technology and low productivity. The use of mobile applications in agriculture can help smallholders access agricultural information and financial services, improve access to markets and enhance visibility for supply chain efficiency. Unfortunately, most farmers have not fully exploited these benefits because of lack of uptake in the use of mobile application technology. This study seeks to explore and examine the current level of use of mobile applications for agriculture in Abia State, Nigeria and the factors that affect the uptake of this technology.

A conceptual model which builds on the extended Technology Adoption Model (TAM2) was empirically estimated using Structural Equation Modelling (SEM) to examine the factors that influence the adoption of mobile applications. Primary data were collected from a sample of approximately 260 farmers. Data were analysed using descriptive statistics and SEM with the help of IBM SPSS and IBM AMOS software.

The study results revealed the current state of mobile application use and the factors that affect the adoption of these applications by farmers. The structural model showed that seven of the direct hypothesised relationships in the research model were supported. Social influence (SI), Perceived usefulness (PU), Information/awareness (IA) and Intention to use (ITU) affected the adoption of mobile applications positively, while perceived risk (PR) and Perceived cost had a negative impact on their adoption.

This study contributed extensively to farmers' technology usage literature through its findings. It proved that extended TAM is a suitable model to explain the factors that influence mobile application adoption behaviour. It helped in bridging the information gap between agricultural application developers and farmers by revealing some important demographic information of farmers such as their age, gender, educational level, the type of farming carried out and most importantly, the factors that affected the adoption and continuing use of mobile applications by farmers.

Keywords: Mobile applications, smartphone, smallholders, ICT adoption, Structural Equation Modelling, Extended Technology Adoption Model, TAM2, SEM

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List of Abbreviations

AGFI	Adjusted Goodness of Fit Index
AMOS	Analysis of Moment Structure
AU	Actual Usage
AVE	Average Variance Extracted
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
COM	Compatibility
CR	Composite Reliability
DIT	Diffusion of Innovation Theory
EFA	Exploratory Factor Analysis
FAO	Food and Agricultural Organisation
GDP	Gross Domestic Product
GES E-wallet	Growth Enhancement Support Electronic wallet
GFI	Goodness of Fit Index
GPS	Global Positioning System
IA	Information/Awareness
ICT	Information Communication Technology
IDC	International Data Corporation
IFPRI	International Food Policy Research Institute
iOS	iPhone Operating System
ITU	Intention to Use
KACE	Kenyan Agricultural Commodity Exchange
KMO	Kaiser-Meyer-Olkin
MSV	Maximum Shared Square Variance
NBS	National Bureau of Statistics
PC	Perceived Cost
PE	Performance Expectancy
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
PR	Perceived Risk
RMSEA	Root Mean Square Error of Approximation
SAP	System Application Products

SE	Satisfaction/Experience
SEM	Structural Equation Modelling
SI	Social Influence
SMC	Squared Multiple Correlations
SMS	Short Message Service
SPSS	Statistical Package for the Social Science
SRMR	Standardized Root Mean Square Residual
TAM	Technology Acceptance Model
TAM2	Extended Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UN	United Nations
USAID	US Agency for International Development
UTAUT	Unified Theory of Acceptance and Use of Technology

CHAPTER ONE

Introduction

1.1 Background

Nigeria is a developing country in West Africa with a population of 195 million (World Population Review, 2018). Agriculture is the base of the country's economy and has remained the main source of livelihood for most inhabitants (FAO, 2017). It has also contributed significantly to the improvement of Nigeria's Gross Domestic Product (GDP) over the last 10 years (Sertoglu, Ugural, & Bekun, 2017). In 2016 and 2017, agriculture dominated the non-oil sector of the economy, contributing 21.26 percent in 2016 and 24.44 percent in 2017 to Nigeria's nominal GDP (National Bureau of Statistics, 2017). According to the National Bureau of Statistics (NBS) in 2005, as cited in Ogunniyi and Ojebuyi (2016, p. 173), over 80 percent of the population lived in rural areas. About 70 percent of the population engaged in agriculture and they are made up of smallholders who cultivate or own farmland less than five hectares (Ofana, Efefiom, & Omini, 2016). These smallholders produce over 80 percent of all agricultural produce in the country.

According to Nwajiuba (2012), Nigeria has about 79 million hectares of arable land, and over 32 million hectares are cultivated for both crop and livestock production. But the current production rate has been unable to feed Nigerian's growing population leading to food security issues and high food import bills. As at April 2018, the population of the country has increased by 1.6 million with an annual growth rate of 2.63 percent (World Population Review, 2018). A review of agricultural productivity in Nigeria by the International Food Policy Research Institute IFPRI (2009) showed that inconsistent provision of farm inputs and services by government, marketing of farm commodities, use of traditional management practices, absence of GPS for livestock productivity, inadequate information on the use of modern technology and practices, as well as poor extension service delivery were among the factors that hindered agricultural productivity. IFPRI findings revealed that these challenges were more pronounced because the majority (80 percent) of farmers in Nigeria are smallholders who cannot afford the cost of using modern technologies and farm practices.

Although agriculture in Nigeria has been of great importance to the economy, it is confronted by most of the challenges that hamper agricultural improvement in developing countries and include: a low level of mechanisation in agriculture, high illiteracy levels among the farmers, lack of credit facilities for farmers, weather vagaries, low technology diffusion, poor infrastructure, inadequate access to markets, defective research and extension services, implementation inefficiency, practice of tenure ownership, pests and diseases and imperfect information (Abutu, 2014; Aker, 2010, 2011; Ofana et al., 2016; UN, 2013). According to Aker, Ghosh, and Burrell (2016), most of the the agricultural problems as described by Abutu (2014), Ofana et al. (2016) and the United Nations (UN) (2013) that hamper agricultural productivity and development in developing countries could be addressed or managed effectively through the use of mobile phone applications by the farmers.

The use of mobile phones has been identified as one of the existing forms of Information Communication Technologies (ICTs) that can improve agricultural productivity and accelerate rural development processes (Asa & Uwem, 2017; Nyamba & Mlozi, 2012; Qiang, Kuek, Dymond, & Esselaar, 2012). Similarly, Chukwunonso and Tukur (2012), in their study carried out in Nigeria, recognised the mobile phone as a form of ICT that can contribute to poverty reduction and socio-economic development through its application in agriculture. In 2006, Torero and Von Braun predicted that mobile phones would be the ICT that will have the greatest diffusion and impact on the poor masses which include rural smallholders. They contend that mobile phones will help to reduce the marginalisation of the poor by promoting communication that is not restricted by time, distance, volume and medium, thereby surmounting the obstacles created by territory and social standing. There has been a growing awareness of the usefulness of mobile phones and this has drawn the attention of individuals, businesses, governmental and non-governmental organisations to the myriad of purposes a mobile phone can serve in various sectors such as agriculture, health, business, education and the entertainment sector (Baumüller, 2012, 2015). In the agricultural sector, Costopoulou, Ntaliani, and Karetsos (2016) highlighted some of the important services that could be achieved through the use of mobile phones which include weather forecasting for farmers, agricultural product market prices, information for agricultural machinery and equipment, agricultural business news, management of irrigation systems, yield forecasting and monitoring, dairy farming, management of agricultural products and crop sensors and registration of soil types. These services can be achieved through smartphones as a smartphone is needed to provide a platform where various mobile applications can be installed before usage.

1.2 Smartphone and mobile applications

Within the last decade, smartphones and mobile applications have become part of peoples' daily lives and most essential in how they carry out their daily activities. It has helped in real-time information acquisition, communication, entertainment and for productive purposes. According to the Pew Research Center (2016), smartphones are mobile phones that can access the internet and support application installation. Qiang et al. (2012) identified some advantages of smartphones over low-end mobile devices which include a touchscreen, a wider user base, delivery of instant information conveniently, affordability, the ability to deliver personalized information to owners, and voice communication support.

Smartphones have witnessed a high rate of adoption worldwide because of their affordability and continuing improvement in functionality (Richard, 2015). The International Data Corporation (IDC) study on smartphone shipments worldwide showed that shipments would reach 1.77 billion units in 2021 from 1.53 billion shipped in 2017, which will result in a compound annual growth rate (CAGR) of 3.8 percent (Scarsella & Stofega, 2017). Similar research by the Pew Research Center (2016) shows that internet usage in developing countries increased from 45 percent in 2013 to 54 percent in 2015 just as smartphone usage increased from 21 percent in 2013 to 37 percent in 2015. It is worth noting that smartphones require internet connectivity for installed applications to function effectively.

Mobile applications (mobile apps) are software programmes designed to run on mobile devices like smartphones and tablets (Costopoulou et al., 2016). They are mostly built to provide users with similar services to those accessible on desktop and laptop computers (PCs). The functions they perform are essential and specific, ranging from productivity, entertainment, and access to information. They are designed to be interactive and easy to use and also provide users with mobile contents such as text, audio, recordings, images, graphics and videos.

Notably, there are six categories of mobile apps which are utility mobile apps, lifestyle mobile apps, games/entertainment mobile apps, social media mobile apps, productivity mobile apps and news/information channel mobile apps (Lane & Manner, 2012; Matteo, 2018). These six categories cover virtually all human activities from business, health, agriculture, entertainment, sports, travel, tourism, education and production to finance (Costopoulou et al., 2016). Most mobile apps designed to aid farmers and agribusiness stakeholders fall under productivity mobile apps, news/information mobile apps and social media mobile apps.

There are various types of operating systems that can be found on a smartphone, and this determines the type of mobile application that could be compatible with or installed in them (Divya & Kumar, 2016). Some of the notable mobile operating systems that run on most smartphones include Android, iOS, Windows and Blackberry. The operating system on a mobile phone has been identified as one of the factors that affect the use of mobile applications by an individual (Lim, Bentley, Kanakam, Ishikawa, & Honiden, 2014). A user with an Android-based smartphone can only install Android-based applications; the same applies to iOS, Windows and Blackberry-based smartphones. In the same manner, an iOS user cannot use an Android mobile application if they cannot find the iOS version of such a mobile application. Studies have shown that Android is the most popular and the most used mobile operating system followed by iOS, Windows and Blackberry (Costopoulou et al., 2016; Divya & Kumar, 2016; Joseph & Shinto Kurian, 2013). According to Divya and Kumar (2016, p. 438), “Android gets 80.7 percent, and it is the best smartphone operating system in the world” because it has an open source operating system which makes it possible for users to install third-party applications from apps stores.

Mobile application developers strive to develop each mobile app on various smartphone operating systems with the aim of reaching a wider user base. Because each operating system has its own distinctiveness, this becomes a challenge to developers because each operating system has a unique coding stream. Therefore technical issues related to mobile operating systems' continuous support, update and design have to be dealt with (Pastore, 2013). When mobile app developers are unable to replicate an app on various mobile operating systems, this becomes an issue that the end users have to deal with because of incompatibility of the operating system. Studies have identified lack of compatibility as one of the main reasons for not adopting or using a mobile application despite its perceived benefits (Al-Jabri & Sohail, 2012; Shaikh & Karjaluoto, 2015).

Studies on the use of mobile applications by farmers is an aspect of technological innovation that has received much attention, but most of these studies tend to generalise the term "mobile phone use" and "mobile phone adoption" without taking into consideration the difference between using a mobile phone and using a mobile phone application (Baumüller, 2015; Richard, 2015). To use a mobile application for any purpose, a person must have a smartphone or a tablet (a mini computer with a mobile operating system). This serves as a platform where applications can be installed before use. Although the smartphone evolved from mobile phones because of advances in technology, a mobile phone is simply a phone used for the primary aim of making and receiving calls and sending text messages. Other useful features found in a mobile phone include a calendar, calculator, alarm, clock, radio, and touch light. But a smartphone offers a wide range of additional services, some of which may be obtained on a desktop or laptop computer. Smartphones are affordable, very portable and easy to operate, with the ability to deliver instant and convenient services (Qiang et al., 2012). This makes them an ideal tool for smallholders. The ability of a smartphone to support mobile applications has made it easier for individuals and businesses to get things done easily and in a timely manner, thereby making them more productive. According to Pastore (2013), companies and businesses that make use of apps on smartphones have been able to stay close to their customers and remain active in their competitive environment. It has also created economic opportunities for employment, learning a new skill, receiving information or medical treatment and even starting a new business (Aker & Mbiti, 2010).

1.3 Use of Mobile Applications for Agriculture in Developing Countries

In most developing countries, the use of mobile phone applications for agricultural purposes is still gaining popularity, while in some developing countries such as India, Kenya, Uganda, South Africa and Tanzania, agricultural productivity has been improved through the use of mobile applications (Qiang et al., 2012). Baumüller (2015) asserted that the use of mobile applications for agriculture has the potential to reach and assist rural smallholders. He went on to confirm that the agricultural sector of most developing countries is characterised by a greater number of smallholders who are often subsistence farmers with obsolete technology and low productivity. A review on the use of mobile applications in developing countries by Hatt, Wills, and Harris (2013) showed that mobile apps had improved health-related services in Asia, while in Africa, mobile money applications have improved financial transactions. According to the World Bank (2017), opportunities abound for agriculture to be enhanced through ICT, by improving market access and value chains, providing information on disease and climate, and facilitating extension service delivery, providing a better market link and distribution channels, as well as access to financial services which include payments, insurance and credits.

Qiang et al. (2012) carried out a study, where they investigated the impact of 92 mobile applications for agriculture and rural development in Africa, Asia, Latin America and the Caribbean (developing countries). They found that most agricultural mobile applications focused more on providing market information, facilitating market links, improving supply chain integration and increasing access to extension services. Among the uses served by the various agricultural apps, valuable information was rated the most important, because of the high level of information asymmetry affecting the rural markets in developing countries (Aker, 2010; Brown, Zelenska, & Mobarak, 2013; Qiang et al., 2012; World Bank, 2017). The mobile applications that improved agricultural supply chain integration facilitated other social and economic benefits including value addition, job creation, reduction in product losses and strengthening of the global competitiveness of developing countries. Figure 1.1 shows the results generated from the various agricultural applications studied by Qiang et al. (2012).

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Figure 1.1 Results generated by mobile applications for agricultural and rural development
source: (Qiang et al., 2012, p. 17)

Results generated by Qiang et al. (2012) showed that use of mobile applications helps smallholders achieve higher incomes, with lower transaction and distribution costs on output sales and input supplies. Both producers and consumers enjoyed improved traceability. Other stakeholders such as financial institutions had new opportunities to explore.

In Sub-Saharan Africa, Kenya has been recognised as the pacesetter in the development of agricultural mobile apps (Baumüller, 2015). This is evident in the number of mobile apps being used by Kenyan farmers and the extensive research that has been carried out on the impact and adoption of these mobile apps (Baumüller, 2013; Kante, Oboko, & Chepken, 2016; Kirui, Okello, Nyikal, & Njiraini, 2013;

Wyche & Steinfield, 2016). The findings showed that Kenyan farmers increased their farm productivity and income by using such mobile apps as Virtual City AgriManager, M-Pesa, KACE (Kenyan Agricultural Commodity Exchange), DrumNet and KilimoSalama. Brown et al. (2013, p. 20) reported that M-Pesa "is the most widely adopted mobile financial service around the world with over 14 million users by early 2011." This represents over 70 percent of Kenya's adult population. However, Gichamba (2015, p. 4) noted that most Kenyan farmers that benefited from these mobile apps were farmers in suburban regions and agriculture intensive areas. Similarly, farmers from Uganda witnessed a positive impact on their farming productivity by using mobile apps like Grameen (weather application), Esoko, Google Trader, WeFarm, Infotrade, Foodnet and Farmgain(Qiang et al., 2012). Evidently,Martin and Abbott (2011) found in their study on the adoption of mobile phone use in Uganda that 87 percent of the farmers used mobile apps for coordination of inputs and 70 percent used them for accessing market information. These services were considered the most important for Ugandan farmers.

Other notable Sub-Saharan African countries witnessing improvement in their agricultural sector through the adoption of mobile apps include Ghana, Tanzania, Botswana and South Africa. Esoko mobile app and Cocoa Link reduced asymmetric information faced by Ghanaian farmers (Aker et al., 2016). Modisar mobile app improved livestock production in Botswana (Chukwunonso & Tukur, 2012). M-Kilimo helped Tanzanian farmers receive extension services and market information that ultimately increased their productivity and income (Temu, Henjewele, & Swai, 2016).

Some of the agricultural mobile apps charge subscribers (farmers) for using the services provided through the mobile apps (Qiang et al., 2012). While some of the mobile apps provide services that are subsidised, some others are completely free of charge, because the services have been paid for or subsidised by either government, donors, private companies, commercial banks or trust funds. The services or content of the mobile apps can either be provided by the government, extension workers, media, or specialised commercial units for mobile money apps, and finally through crowdsourcing where the farmers can contribute all the useful information at their disposal. Crowdsourcing is typical of such social media apps as Twitter, WhatsApp and Telegram.

Mobile applications have also created business opportunities for companies with an interest in improving agricultural productivity in developing countries (Baumüller, 2015). In India, Nokia and Reuters Thomson are providing information services to farmers (Saravanan & Bhattacharjee, 2014). In Uganda, Google is connecting producers to consumers through an internet-based platform (Ssekibuule, Quinn, & Leyton-Brown, 2013). In Ghana, a German software company "System Application Products" (SAP), is overseeing supply chain management systems for smallholders (Baumüller, 2015). In Tanzania, Vodafone Group, US Agency for International Development (USAID) and TechnoServe have partnered to boost agricultural productivity and incomes of farmers in Tanzania through the use of mobile technology (Vodafone Group, 2014).

These studies highlight the potential of mobile phone apps to improve agricultural productivity and therefore the need to understand more about the use of mobile phone application technologies by farmers in developing countries.

Looking at the impact assessment of the use of mobile apps for agriculture in developing countries, a good number of studies have been conducted on assessing the impact of mobile phones in developing countries (Aker & Mbiti, 2010; Chhachhar & Hassan, 2013; Martin & Abbott, 2011), with just a few having focused on agricultural mobile applications' adoption and impact.

1.4 Adoption of Mobile Applications by Farmers in Nigeria

The mobile phone industry in Nigeria has played a significant role in the socio-economic development of the country by creating a platform for innovation, digital inclusion, and access to information exchange, finance, markets and governance to millions of citizens who have been excluded from these services (Brown et al., 2013; GSMA, 2016; Ogunniyi & Ojebuyi, 2016). Unfortunately, most farmers have not fully exploited these benefits because of lack of uptake in the use of mobile application technology (Chhachhar, Chen, & Jin, 2016). Mobile phone technology is a crucial factor that can contribute to poverty reduction and economic development through its application in agriculture (Baumüller, 2012). The level of internet usage in Nigerian has been increasing and according to the Pew Research Center (2016, p. 15), "in 2014, 38 percent of Nigerian internet users said they access the internet several times a day. In 2015, the number increased to 58 percent." The number of smartphone users in Nigeria is estimated to reach 23.3 million by 2019 from 11 million in 2014 (Statista, 2018). Despite this significant increase in smartphone and internet usage, there is still a prevalent digital divide in developing countries where social and economic inequalities still affect the access, use and impact of ICTs (Ohemeng & Ofosu-Adarkwa, 2014).

In Nigeria, the number of mobile apps that could aid agricultural productivity is increasing, and there are some that are still at their development stage with the web version already in existence and running. Notable mobile apps for agriculture in Nigeria include apps such as GES E-wallet, which stands for Growth Enhancement Support Electronic wallet. It was created by the Ministry of Agricultural and Rural Development in Nigeria to provide soft loans to farmers, track seed and fertiliser disbursement and educate farmers on farming methods that will improve their output (Uwalaka, 2017). Agrikore is another mobile app that connects farmers, agro-dealers, commodity traders and insurers under a platform that ensures transparency and honesty among the actors in the system. Verdant mobile app offers market information and general agricultural guidance and Agrodata is dedicated to providing agricultural information and research data. Hello Tractor app helps farmers access tractors and other farming tools. Probityfarms is used for farm management as well as to connect farmers to market and Compare-the-market is designed to compare the price of food crops and livestock in Nigeria on a daily basis. Cellulant app works in partnership with the federal government of Nigeria to help farmers redeem subsidised seed and fertiliser vouchers from designated retail outlets. Farmers use WhatsApp and Telegram to create informal groups where information and ideas are exchanged. Various Nigerian mobile banking apps are designed to ease payments and other financial transactions on-the-go. Although there are a significant number of mobile apps that can help farmers, the use of these is low especially by small farmers.

1.5 Research Problem

Agriculture has been identified as the main source of livelihood for most Nigerians (FAO, 2017), where 70 percent of the population engages in agriculture, and they are mainly smallholders who produce on a small scale. These smallholders produce over 80 percent of the countries' entire agricultural output which is not enough to feed the growing population of Nigeria, leading to over-dependence on imported food (Nwajiuba, 2012). The main challenges faced by these smallholders are access to agricultural information, access to market and access to financial services (Baumüller, 2012; Nwajiuba, 2012). Studies have proven that the use of mobile application in agriculture can help smallholders access agricultural information and financial services, improve access to markets and enhance visibility for supply chain efficiency (Aker & Mbiti, 2010; Baumüller, 2015; Qiang et al., 2012; Vodafone Group and Accenture, 2011)

According to Lim et al. (2014), there has been little research carried out on the behaviours of mobile app users and their mobile devices. They found in their study that lack of user feedback and inability to understand app users' behaviour caused many mobile apps to fail as app users seldom give user feedback or reviews irrespective of the level of satisfaction derived (McIlroy, Shang, Ali, & Hassan, 2017). Lim et al. (2014) went ahead to reveal that app developers lack important demographic information about users such as their age, gender, educational level and income level. This makes it difficult to understand the usage pattern of these apps.

Ogunniyi and Ojebuyi (2016), conducted a study on the use of mobile phones for agribusiness by farmers in Southwest Nigeria, where they found that 76 percent of farmers mostly use mobile phone radio and 83 percent use their phone just for calls. However, the study did not take into consideration the use of agricultural mobile apps by farms as they only focused on such utility tools as SMS, calls, calendar, alarm, radio etc. that have been displaced by a vast range of more advanced technological options (Richard, 2015). The factors that affect the use of agricultural mobile apps were overlooked in their study.

A study carried out by Asa and Uwem (2017) in South-south Nigeria revealed that 90 percent of the rural farmers had mobile phones and 98 percent had access to mobile phones, but the study failed to capture the type of phones that the farmers use and the operating system installed on such mobile phones. Similarly, Jaji, Abanigbe, and Abass (2017) in their study carried out in South-west Nigeria revealed a 98 percent mobile phone ownership and usage, mostly for accessing information. However, their study also did not clearly capture how this information was being accessed. There is the need to understand the kind of phone and mobile apps used by farmers and the factors that influence farmers' willingness to use mobile apps.

Chukwunonso and Tukur (2012) in their study on the adoption of ICT in agriculture in Nigeria discovered that ICT cost, lack of access and awareness, lack of end-user information exchange and trust were among the factors that affected ICT adoption. Their study looked at ICT from a broader point of view. This included computer acquisition, software installations and internet access, which the farmers considered to be expensive. Smartphones are less expensive, and mobile apps are easier to access from app stores. Studies have shown that adoption of mobile apps by consumers is mostly influenced by ease of use, trust, performance expectancy, cost and social influence (Chukwunonso & Tukur, 2012; Malik, Suresh, & Sharma, 2017; Shaikh & Karjaluoto, 2015). On the other hand, Xu, Frey, Fleisch, and Ilic (2016) and Lane and Manner (2012) discovered in their study that mobile app adoption is influenced by the user's personality traits and not about the perceived benefits or costs of the app. They discovered that extroverted individuals preferred gaming, entertainment and social media mobile apps. To them, productivity apps were less important, while conscientious individuals would rather go for productivity apps and information apps. Unal, Temizel, and Eren (2017) study on mobile apps adoption shows that gender influences the choice of apps downloaded by individuals. These findings show the need for a better understanding of how farmers perceive the use of mobile apps.

Most of the studies on the use of mobile phones in agriculture in Nigeria have approached the concept from a generalised point of view (Aker, 2010; Asa & Uwem, 2017; Chhachhar et al., 2016; Ogunniyi & Ojebuyi, 2016). There has been no distinction between a mobile phone and a smartphone, between utility tools/apps and productive mobile apps, or between information mobile apps and social media mobile apps. They have all been categorised as "the use of mobile phone in agriculture". In essence, there are clearly defined differences between these terminologies. Most agricultural mobile apps fall under the category of productivity mobile apps, information mobile apps and social media mobile apps. These three categories of mobile apps have been designed to function only on a smartphone.

Furthermore, existing literature on the use of mobile phones in Nigeria has not captured farmers' perceived interest and willingness to use mobile apps. There is also the need to bridge the information gap between agricultural app developers and app users. Quantitative analysis will help to provide the farmers' demographic and socioeconomic characteristics and how they affect farmers' use of smartphones and mobile apps.

1.6 Research Objectives

So far, the findings from earlier studies on the use of mobile applications by farmers in Nigeria are insufficient to conclude that farmers are using mobile applications and that they have improved their productivity. To help address this gap, this research is aimed at providing a critical understanding of the current state of mobile apps use in the Nigerian agricultural sector by examining the factors that affect the adoption of mobile applications. It also seeks to contribute to mobile apps use literature by exploring and examining the current level of use of mobile apps for agriculture in Abia State and the factors that affect the uptake of this technology. To successfully achieve this fit, this study will seek to provide answers to the following research questions:

I. What are the factors that influence the adoption of mobile apps by farmers?
II. Why are some farmers not adopting mobile apps?

Answers to these questions are required to determine the factors that influence the adoption of mobile apps by farmers in Abia state, Nigeria.

The specific objectives are to:

I. Investigate the types of phones and the operating systems on the phones used by farmers;
II. Identify the current mobile applications being used by farmers and their uses;
III. Identify the factors that distinguish farmers who use mobile apps apart from those who do not use them;
IV. Examine the interest and willingness of farmers to use mobile apps in their daily farming activities; and

V. Determine the factors that influence the adoption of mobile apps.

CHAPTER TWO

Literature Review

2.1 Theories of Technology Adoption

Mobile application development in the area of mobile communication technology has advanced considerably in the last decade with much improvement in the services and functions obtainable in these mobile applications (Costopoulou et al., 2016; Qiang et al., 2012). The agricultural sector, just as other sectors including finance, education, and entertainment, has witnessed the development of mobile apps to aid farmers in their daily farming activities (Suarez & Suarez, 2013). But the main challenge faced by developers of these apps is to get farmers to adopt and use these applications developed for them (Richard, 2015). To understand and solve this problem of adopting new technology, researchers have developed theories and models that try to explain the rationale behind adopting or rejecting a new technology which has implications for both the developer and the intended users of this technology (Al-Jabri & Sohail, 2012; Lai, 2017; Malik et al., 2017). Some of the empirical theories are: Theory of Diffusion of Innovation (DIT) (Rogers, 2010), Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), Theory of Planned Behaviour (TPB) (Ajzen, 1991), Technology Acceptance Model (TAM) (Davis, 1989; Sharma & Mishra, 2014), Technology Acceptance Model (TAM2) (Venkatesh & Davis, 2000) and Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh, Morris, Davis, & Davis, 2003). See Table 2.1 for empirical studies.

2.1.1 Diffusion of Innovation Theory (DIT)

Diffusion of Innovation Theory (DIT) was developed by Rogers in 1960 (Sharma & Mishra, 2014). According to Lai (2017, p. 22), "Rogers proposed that diffusion of innovation theory was to establish a foundation for researching innovation acceptance and adoption". Rogers (1995) reviewed over 508 diffusion studies before establishing Diffusion of Innovation Theory for the adoption of innovations among individuals and organisations. Rogers went ahead to explain the importance of the process and channel through which an innovation is communicated over time among the members of a social system. This process and channels were what he referred to as “diffusion”. Lai (2017) described this process of communicating innovation to include understanding, implementation, persuasion, decision and confirmation, which will lead to the development of Rogers (1995) S-shaped adoption curve of innovators, early adopters, early majority and laggards, as can be seen in Figure 2.1. The „S‟ shaped curve represents the cumulative rate of adoption (or diffusion curve). The bell curve depicts the number of new adopters along the same timeline. In an attempt to understand factors that influence adoption of ICT tools, which include mobile phone applications, DIT seem to be the most used theory (see Table 2.1) (Al-Jabri & Sohail, 2012; Genius, Koundouri, Nauges, & Tzouvelekas, 2013; Martin & Abbott, 2011). According to Al-Jabri and Sohail (2012), DIT is a theory that attempts to analyse how, why and at what rate a new technology and concept spread.

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Figure 2.1 Innovation adoption curve
Source: (Briscoe, Trewhitt, & Hutto, 2011)

2.1.2 Theory of Reasoned Action (TRA)

TRA was developed by Fishbein and Ajzen (1975), and it is one of the oldest and most popular theories (Lai, 2017). According to Malik et al. (2017, p. 107), in TRA, “intention determines behaviours and attitudes influence this intention and in turn behaviour” (See Fig. 2.2). The theory defines the links between intentions, beliefs, norms, attitude and behaviours of persons. Fishbein and Ajzen (1975) defined attitude as a person’s positive or negative feeling about carrying out a specific action and defined “belief” as a link between an object and some attribute and “behaviour” as a result of intention. A key factor in TRA is a person’s subjective norms which determine how they perceive their community's attitude to a certain behaviour or what others will think of a certain behaviour (Lai, 2017) (e.g. "My fellow farmers are using mobile money app and it is prestigious to have one").

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Figure 2.2 Theory of Reasoned Action (TRA)
Source: (Fishbein & Ajzen, 1975)

2.1.3 Theory of Planned Behaviour (TPB)

TPB was developed by Ajzen (1991). The theory argues that the performance of a person's behaviour of interest is influenced by their behavioural, normative and control beliefs. This leads them to carry out a certain behaviour (Malik et al., 2017; Sharma & Mishra, 2014). As can be seen in Figure 3, attitude, just as in TRA is believed to have a positive or negative influence in one's life. Subjective norms mean that people act in a certain way because of what other people think or say. The last factor is perceived behavioural control which is the control people perceive may limit their behaviour (Lai, 2017) (e.g. "Am I eligible to apply for mobile money apps and what are the requirements?"). The theory predicts that attitude, favourable social norms and high levels of perceived behavioural control are the best predictors for forming a behavioural intention, which in turn leads to certain behaviour or act (see Figure 2.3)

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Figure 2.3 Theory of Planned Behaviour (TPB)
Source: (Ajzen, 1991)

2.1.4 Technology Acceptance Model (TAM)

TAM was developed by Davis (1986) for his doctoral proposal, and it was developed specifically for the analysis of users' acceptance of Information Communication Technologies (ICTs) (Lai, 2017). Davis (1989) used this model to test two specific beliefs which are Perceived Usefulness and Perceived Ease of Use. He was of the opinion that Perceived Usefulness is a potential user's subjective likelihood that makes them believe that using a particular technology or mobile app will improve their action while Perceived Ease of Use is the degree to which the potential user expects the technology to be easy or effortless to use (see Figure 2.4). Davis (1989) contends that a person's belief in a technology may be influenced by other external factors or variables. King and He (2006) used the TAM model for analysis and found it very useful and applicable in other areas of study, while Benbasat and Barki (2007) criticised the TAM model, citing that it has a lot of limitations when applied in a rapid-changing IT environment.

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Figure 2.4 Technology Acceptance Model (TAM)
Source: (Davis, 1989)

2.1.5 Extended Technology Acceptance Model (TAM2)

Technology Acceptance Model (TAM 2) was developed by Venkatesh and Davis (2000). It is a modification of TAM. Their study provided more key determinants that could influence a user's perceived usefulness and intention to use in their extended TAM model. According to Sharma and Mishra (2014), the key determining factors included are social influence processes (which involve image, voluntariness and subjective norm) and cognitive instrumental processes (which include perceived ease of use, output quality, job relevance and result demonstrability), as can be seen in Figure 2.5.

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Figure 2.5 Extended Technology Acceptance Model (TAM2)
Source: (Venkatesh & Davis, 2000)

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

UTAUT was developed by Venkatesh et al. (2003) after studying and reviewing the previous technology adoption models and their constructs. They aimed to come up with a comprehensive model that could be applied to a broad area of applications. The model proposed four key constructs which predict users' behavioural intention. The key constructs are "Performance Expectancy, Effort Expectancy, Social Influence and Facilitating Conditions", as can be seen in Figure 2.6. These four proposed key constructs were theorised after testing the constructs used in the previous models, and they were found to be the most significant factors that affect the intention to use information technology. The first construct in UTAUT (Performance Expectancy) is derived from five similar constructs from previous models which are Perceived Usefulness, Relative Advantage, Extrinsic Motivation, Job-Fit and Outcome Expectations, while Perceived Ease of Use and Complexity make up Effort Expectancy.Venkatesh et al. (2003) found Social Influence was not significant in voluntary contexts.

According to Sharma and Mishra (2014), previous theories on technology adoption explained just 30-40 percent variance in adoption behaviour while UTAUT explained 70 percent of the variance, making it the superior model. However, Van Raaij and Schepers (2008) and Casey and Wilson-Evered (2012) criticised UTAUT on the basis of being too complex, not being parsimonious in its approach and unable to justify individual behaviours. Williams, Rana, Dwivedi, and Lal (2011) reviewed 450 articles that cited UTAUT, and they found that only a small number of these articles used UTAUT constructs in their study; instead, they used it in developing their theory.

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Figure 2.6 Unified Theory of Acceptance and Use Theory (UTAUT)
Source: (Venkatesh et al., 2003)

Table 2.1 Theories used in ICT adoption studies and their findings

Author	**Topic**	**Theory/Model**	**Dependent variables**	**Independent variables**	**Findings**
Malik et al. (2017)	Factors influencing consumers' attitudes towards adoption and continuous use of mobile applications: a conceptual model	Adoption and continuous use model	Satisfaction and Habit as mediating variables	Performance Expectancy, Ease of Use, Social Influence, Enjoyment, Incentive, Facilitating Condition, Aesthetics, Trust	Satisfaction is the most important predictor of intention to repurchase an app. Perception after adoption leads to continued use, and Habit is a crucial determinant that leads to continued usage of an information system (IS).

Gichamba (2015)	The Extent of ICT Adoption by ACP Farmers: mAgriculture Adoption in Kenya	Revenue Model		Cost, Network Availability, Language Barrier, Privacy, Risk-Averse	Most farmers were sceptical and wanted to see that applications were working before they would adopt them. Cost, Network Availability and Language Barrier were the predominant challenges that hindered adoption.
Lin (2011)	An empirical investigation of mobile banking adoption: The effect of innovation attributes and knowledge-based trust	Innovation Diffusion Theory and Knowledge-Based Trust Model	Attitude and Behavioural Intention of adopting	Perceived Relative Advantage, Ease of Use, Compatibility, Perceived Competence, Benevolence and Integrity	Perceived Relative Advantage, Ease of Use, Compatibility, Competence and Integrity significantly influence Attitude, which in turn lead to Behavioural Intention to adopt (or continue-to-use) mobile banking
Al-Jabri and Sohail (2012)	Mobile banking adoption: Application of diffusion of innovation theory	Diffusion of Innovation Theory	Mobile banking adoption	Relative Advantage, Complexity, Compatibility, Observability, Trialability, Perceived Risk	Observability, Relative Advantage and Compatibility affected adoption positively. Perceived Risk affected adoption negatively, while Complexity and Trialability had no

					significant effect on adoption.
Fathema (2013)	A Structural Equation Modelling of an Extended Technology Acceptance Model for faculty acceptance of Learning Management Systems (LMSs)	Extended Technology Acceptance Model (TAM2)	Behavioural Intention to Use and Actual Usage	System Quality, Perceived Self-Efficacy, Facilitating Conditions, Perceived Usefulness, Perceived Ease of Use, Attitudes Towards Using, Behavioural Intention to Use	The study result showed that System Quality, Perceived Self-efficacy and Facilitating Conditions had a significant effect towards the use of canvas. The study proposed 13 hypotheses of which 11 were supported by the results.
Chan et al. (2011)	Modelling Citizen Satisfaction with Mandatory Adoption of an E-Government Technology	UnifiedTheory of Acceptance and Use of Technology (UTAUT)	Satisfaction	Awareness, Compatibility, Self-Efficacy, Flexibility, Avoidance of Personal Contact, Trust, Convenience, and Assistance. Mediating variables (Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions)	Performance Expectancy, Effort Expectancy and Facilitating Conditions were found to have a strong impact on Satisfaction while Social Influence was not significant in determining Satisfaction.
Zaremohzzabieh et al. (2015)	A test of the technology acceptance model for understanding the ICT adoption behaviour of rural young entrepreneur	Technology Acceptance Model (TAM)	Entrepreneurial intention.	Perceived ease of use, perceived usefulness, and behavioural intention. Attitude as a mediator	Perceived Usefulness impacted the adoption of ICT significantly rather than Perceived Usefulness. Improving job

					performance was of more importance to the rural entrepreneurs .
Abdekhoda, Dehnad, Mirsaeed, and Gavgani (2016)	Factors influencing the adoption of E-learning in Tabriz University of Medical Sciences	UnifiedTheory of Acceptance and Use of Technology (UTAUT)	Usage	Performance Expectancy, Effort Expectancy, Social Influence, and Fascinating Condition. Behaviour Intention as a mediating variable	Social Influence, Effort Expectancy and Performance Expectancy affected the faculty members' behaviour towards adopting e-learning while Facilitating Condition had no effect on it.
Hsu, Lu, and Hsu (2007)	Adoption of the mobile Internet: An empirical study of multimedia message service (MMS)	Innovation Diffusion Theory (IDT)	Intention to adopt MMS	Relative Advantage, Perceived Ease of Use, Compatibility, Trialability, Image, Visibility, Result Demonstrability and Voluntariness	Perceived Ease of Use changed at various stages of innovation diffusion. They also found a significant difference between potential adopters and users.

Source: Author's work

2.2 Proposed Extended Technology Adoption Model TAM2 for the Adoption of Mobile Applications by Farmers

TAM, which was first introduced by Davis in 1989 has been used in many studies to successfully analyse and interpret the adoption of various Information Communication Technologies (ICT) in different work environments (Kripanont, 2007; Tarhini, 2013). Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) were the two main factors used in TAM to explain the acceptance or rejection of information technology by a person. PU is said to influence adoption if a user believes that using a technology will enhance or improve their job performance, while PEOU is said to influence adoption if a user believes that a technology would be easy to use. The original TAM model was extended in an effort to apply TAM beyond the workplace environment and into other diverse environments such as entertainment e.g. mobile games (Chen, Rong, Ma, Qu, & Xiong, 2017), consumer services e.g. mobile commerce (Wu & Wang, 2005) and mobile internet (Kim, Chan, & Gupta, 2007). The first major extension was carried out by Venkatesh and Davis (2000) who tested four different systems in four organisations. They referred to the extended TAM model as TAM2. The major difference between TAM and TAM2 is the inclusion of social influence processes and cognitive instrumental processes which they found to significantly affect user acceptance.

According to Venkatesh (2000), the application of TAM outside workplace environments has always encountered problems because the main TAM constructs do not adequately demonstrate how well a technology meets the needs of the work environment and its tasks. Similarly, Bagozzi (2007) contended that TAM overlooks important aspects of technology adoption such as groups' social and cultural aspects. In support of the first major extension of TAM made by Venkatesh and Davis (2000), many researchers have emphasised the need to add more variables to TAM for the purpose of establishing a stronger model (Legris, Ingham, & Collerette, 2003; Wu & Wang, 2005). As a result of this argument, many studies have come up with various extended versions of TAM to suit the work environment and the nature of the technology being studied. These studies build upon the original TAM and TAM2 and modify it by adding or removing constructs to better explain the adoption of a technology in a given setting. e.g. (Chen et al., 2017; Hakkak, Vahdati, & Biranvand, 2013; Park & Kim, 2014; Venkatesh & Davis, 2000; Wentzel, Diatha, & Yadavalli, 2013).

2.2.1 Theoretical Model

This study is on mobile applications which are an aspect of Information Communication Technology (ICT), with a focus on what influences their adoption by Nigerian farmers. The workplace environment in an agricultural setting is quite different from the organisational setting in which TAM and its extended version were first applied by Davis (1989) and Venkatesh and Davis (2000) respectively. The reason for adopting the extended TAM is its ability to successfully explain and predict the adoption of information technologies. Rather than sticking to the original TAM or TAM2 constructs, this study will modify TAM by adding additional constructs that best describe farmers and their farming activities and environment. The three main factors considered in formulating these constructs are farmers' socioeconomic characteristics, their biophysical environment and the nature of their farming operations. These three factors were first examined by Baumüller (2012) in his study on the facilitation of agricultural technology adoption among poor farmers. Although TAM has been modified to suit the study setting, the modification is based on the original extended TAM.

Five main original extended TAM constructs were retained in the study model (Perceived Usefulness, Perceived Ease of Use, Intention to Use, Actual Usage and Social Influence), while six additional constructs were added to modify the original extended TAM to suit the study setting. The six added constructs are Performance Expectancy, Perceived Risk, Perceived Cost, Satisfaction/Experience, Compatibility and Information/Awareness as shown in Figure 2.7. These constructs were carefully selected from reviewed literature on mobile applications and farmer technology adoption studies.

2.2.1.1 Perceived Usefulness (PU)

PU is one of the two main TAM constructs introduced by Davis (1989) to determine a user's acceptance or rejection of information technology. Davis (p.26) defined it as "the degree to which an individual believes that using a particular system would enhance his or her job performance." In the context of farmers' acceptance of mobile applications, PU is defined as the relative advantage a farmer expects to gain from using a mobile app. Apart from Davis (1989) and Venkatesh and Davis (2000), many other studies on ICT use have proved that PU has a significant positive impact on a user's behavioural intention to use an IT or a system (Kesharwani & Singh, 2012; Park & Kim, 2014; Wentzel et al., 2013). This study hypothesises that PU has a direct positive impact on a farmer's Intention to use mobile applications.

2.2.1.2 Perceived Ease of Use (PEOU)

PEOU is the second main TAM construct introduced by Davis (1989) to determine a user's acceptance or rejection of information technology. Davis (p.26) defined it as "the degree to which an individual believes that using a particular system would be free of physical and mental effort." In the context of farmers' acceptance of mobile applications, PEOU is defined as a farmer's assessment of how effortless it is to use a mobile app. Davis noted that PEOU can influence PU because a person who perceives a technology as easy to use would be more likely to perceive it as useful. Most smartphones come with a user-friendly interface. However, Aker et al. (2016) noted that despite the user-friendly interface on most smartphones, farmers with low literacy levels still find it difficult to use a mobile app which can influence their adoption decision. Another factor influencing ease of use is the language barrier. Kaur and Dhindsa (2018) noted that farmers who cannot understand the English language found it difficult to use mobile applications. This study hypothesises that first, PEOU has a direct effect on the PU of mobile apps and secondly PEOU also has a positive significant effect on a farmer's Intention to use mobile applications.

2.2.1.3 Intention to Use (ITU)

ITU is one of the constructs in Venkatesh's extended TAM which was originally introduced by Fishbein and Ajzen (1975) in their Theory of Reasoned Action (TRA). Prior to the extension of TAM, Davis (1989) in the original TAM theorised that a for potential user's behavioural ITU a particular technology is hypothesised to be a major determining factor in whether or not he actually uses it. The theory also has it that a person's behavioural intention to use a given technology is influenced by two beliefs: PU and PEOU. In the study context, a farmer's behavioural ITU mobile apps would be a major determinant of whether he eventually uses them. This study hypothesises that ITU has a significant positive effect on the Actual Usage of mobile apps.

2.2.1.4 Social Influence (SI)

SI is a widely recognised factor that influences a person's technology acceptance behaviour. It was a factor used in Fishbein and Ajzen (1975) Theory of Reasoned Action to explain subjective norms.

Fishbein and Ajzen (p.302) defined SI as a "person's perception that most people who are important to him think he should or should not perform the behaviour in question." In Venkatesh and Davis (2000) extended TAM, SI was used as a key determinant of TAM's PU and ITU constructs. Unlike Fishbein and Ajzen, Venkatesh and Davis used Subjective Norm as one of the factors in explaining the SI process. Subsequent studies on technology adoption (Al-Gahtani, 2016; Hakkak et al., 2013; Taylor & Todd, 1995) have used Subjective Norm and Social Influence interchangeably to explain the impact of other people's views and opinions on the adoption of information technology. Kesharwani and Singh (2012) argued that interchanging Social Influence and Subjective Norm has led to mixed results and the effect on technology adoption has been inconsistent. In most farming communities, especially in developing countries, social interactions exist within the farmers and would be necessary to see the impact on their PU of mobile applications and their ITU mobile apps. According to Hakkak et al. (2013), such an impact could be favourable or unfavourable. This study, therefore, hypothesises that SI has a significant positive impact on the PU of mobile applications.

2.2.1.5 Performance Expectancy (PE)

The PE construct was introduced by Venkatesh et al. (2003) in their Unified Theory of Acceptance and Use of Technology (UTAUT). They described it as the degree to which any technology can improve the productivity of a user or will assist the user to achieve gains in job performance. Consumers tend to adopt and use applications that they perceive would improve their productivity based on their knowledge of the content of the app. In Malik et al. (2017), PE was found to have a significant effect on adoption, especially on male consumers while Chan et al. (2011) reported that PE leads to continued use when satisfaction is derived from initial use. This study hypothesises that PE has a significant and positive impact on the PU of mobile applications.

2.2.1.6 Perceived Risk (PR)

PR is one of the external variables included in the study's extended TAM. It has been in use as early as the 1960s to explain consumers' attitudes towards decision making (Bauer & Cox, 1967). They defined PR with regard to the insecurity and unfavourable outcomes associated with consumers' expectations.

Internet applications are associated with diverse kinds of risk and as a result, consumers are careful when indulging in such. PR has been mostly used in internet and mobile banking transaction adoption study because of the security concerns associated with such transactions (Al-Jabri & Sohail, 2012; Kesharwani & Singh, 2012; Wentzel et al., 2013). Most of these studies found PR to negatively influence users' behavioural intention to use such services. The present study takes into consideration all mobile applications that could be used by farmers, including mobile banking apps, hence the inclusion of PR in the study model. This study hypothesises that PR has a significant and negative impact on the PU of mobile applications.

2.2.1.7 Perceived Cost (PC)

PC is another important addition to the study to extend TAM. Some mobile applications come with a monetary price which must be paid by a user before downloading the app from an app store. Adoption is affected when there is a price attached to the mobile application. Wu and Wang (2005) maintained that the cost-benefit pattern is important to both PU and PEOU in TAM. When there is an excessive cost involved in using an application, such as subscription fees or high internet charges, the adoption rate of such an app is usually low (Qiang et al., 2012). According to Brown et al. (2013), most smallholders are price sensitive so any little change in service fee can drastically affect the adoption rate. Studies have found PC to negatively influence ITU and AU of internet applications (Kim et al., 2007; Wu & Wang, 2005). This study hypothesises that PC has a significant and negative impact on the PU of mobile applications.

2.2.1.8 Satisfaction/Experience (SE)

SE is the level of satisfaction a potential app user derived from previous apps usage experience. This construct proposes that a farmer who derived satisfaction from previous mobile applications usage experience will tend to adopt new technology, contrary to a dissatisfied user. Wang, Yu, Yang, Miao, and Ye (2017) found prior experience to be significant in the adoption of electric cars as customers who had the opportunity to use an electric car were more willing to buy one. Similarly, Kisanga and

Ireson (2015) identified experience as having a high impact on the adoption of e-learning. This study hypothesises that SE has a significant impact on the PU of mobile applications.

2.2.1.9 Compatibility (COM)

COM is one of the five innovative characteristics introduced by Rogers (1995) in his theory of Diffusion of Innovation. According to Wu and Wang (2005, p. 721), "COM is the degree which an innovation is perceived to be consistent with a potential users' existing values, previous experiences and needs." In the context of farming mobile applications, COM is examined on the basis of farming style, type of phones and the operating system on a phone used by a farmer. These three attributes have to be compatible for him to use mobile apps in his farming activities. Wu and Wang (2005) and Chan et al. (2011) in their studies found COM to positively influence PU of information technology. In this study, it is hypothesised that COM has a significant impact on the PU of mobile applications.

2.2.1.10 Information/Awareness (IA)

IA is a very important construct included in the study's extended TAM. A few researchers have included this construct in their technology adoption studies, (e.g. Al-Somali, Gholami, and Clegg (2009) and Hakkak et al. (2013) on online banking adoption, Chan et al. (2011) on the adoption of e-government technology and Costopoulou et al. (2016) on the use of mobile application by farmers). They all found IA to have a significant impact on a person's attitude towards the use of these technologies. IA is regarded as the prerequisite for the adoption of any technology and in the study context, a farmer has to be aware of the existence of an application before he can decide to use it. Such information could be from fellow farmers, media outlets or extension agents. Farmers also seek information regarding the suitability of an app and the potential risks associated with the use of such an app (Baumüller, 2012). According to Aker (2011), asymmetric and costly information is a major issue in the adoption of new technology. Costopoulou et al. (2016) found that 95 percent of Greek farmers did not use mobile agricultural apps because they were not aware of their availability. Therefore, IA is hypothesised to have a significant positive impact on the PEOU of mobile apps and a significant positive impact on the AU of mobile apps.

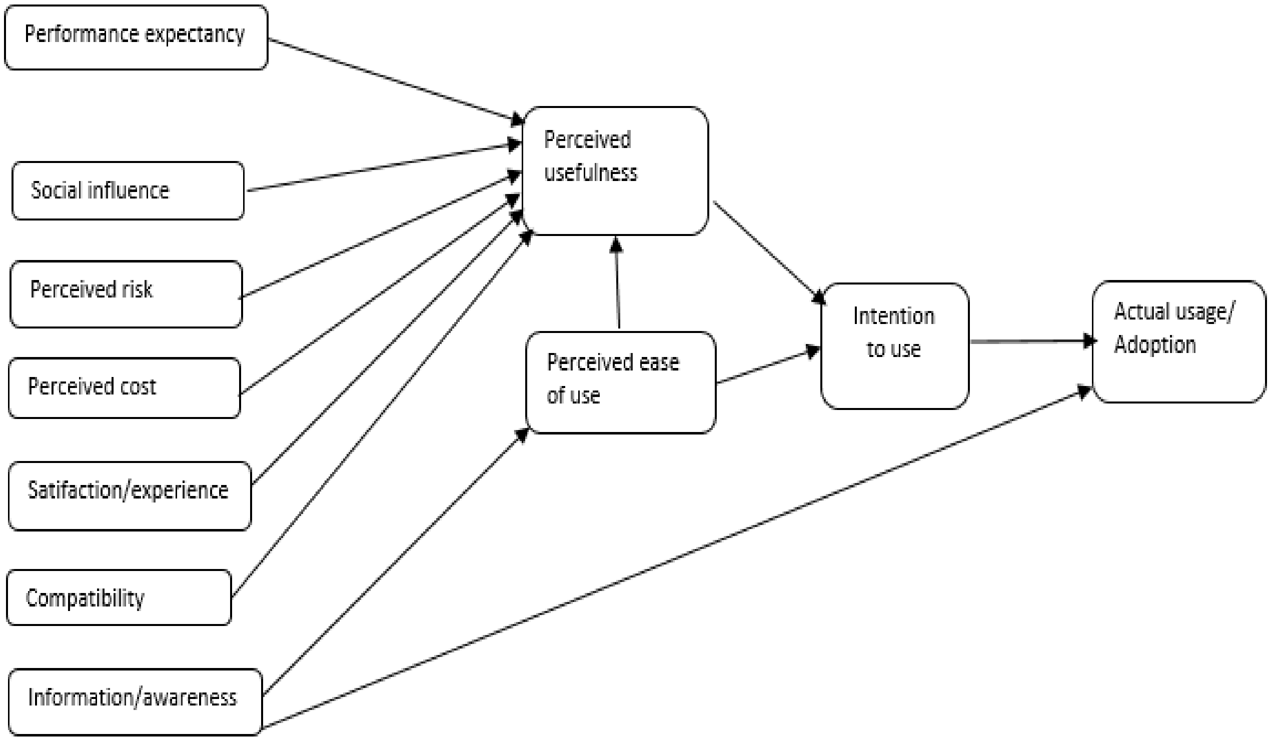

Figure 2.7 Research Model
Source: Author's work

CHAPTER THREE

Methodology

3.1 Introduction

This section describes the study's analytical framework, the study area, the method used for data collection and the type of data collected for the study, and from whom data were collected. The study proposes a conceptual model for the adoption of three types of mobile applications which are productivity mobile apps, information/news mobile apps and social media mobile apps. This model builds on the extended Technology Adoption Model (TAM2) developed by Venkatesh and Davis (2000) which has a high explanatory power (R^2)[1] that enables the strength of the relationship between the dependent and independent variables to be successfully measured (Eisenhauer, 2009). The study proposes PU and PEOU as the mediating variables which explain the relationship between the independent and dependent variables.

3.2 Research Model and Hypotheses

This study adopts Venkatesh and Davis (2000) extended Technology Adoption Model (TAM2) because it has the ability to successfully explain and predict the adoption of information technologies and also it allows the inclusion of external variables which studies (Fathema, 2013; Tarhini, Hone, & Liu, 2013) have shown to have a significant impact on technology adoption. Seven external variables included in this study are Performance Expectancy (PE), Social Influence (SI), Satisfaction/Experience (SE), Perceived Risk (PR), Perceived Cost (PC), Compatibility (COM), and Information/Awareness (IA). This study examined how these external variables (constructs) affect the two important TAM constructs (Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)) which in turn impact the dependent variables (Intention to Use (ITU) and Actual Usage/Adoption (AU)).

[1]Explanatory Power (R^2) measures the "strength of the relationship between the dependent and independent variables."(Eisenhauer, 2009, p. 42). In the science field, statistical models are used for causal explanations and if a model possess a high R^2, such a model is assumed to possess predictive power (Shmueli, 2010).

The study proposes the following hypotheses which were tested using the Structural Equation Modelling (SEM) technique (see Table 3.1).

Table 3.1 Hypotheses formulation

	Hypotheses
H1	Perceived usefulness (PU) has a significant and positive impact on a farmer's intention to use mobile applications.
H2	Perceived ease of use (PEOU) has a significant and positive effect on the perceived usefulness of mobile applications.
H3	Perceived ease of use (PEOU) has a significant and positive effect on a farmer's intention to use mobile applications.
H4	Intention to use (ITU) has a significant and positive effect on the actual usage of mobile apps.
H5	Social influence (SI) has a significant and positive impact on the perceived usefulness of mobile applications.
H6	Performance expectancy (PE) has a significant and positive impact on the perceived usefulness of mobile applications.
H7	Perceived risk (PR) has a significant and negative impact on the perceived usefulness of mobile applications.
H8	Perceived cost (PC) has a significant and negative impact on the perceived usefulness of mobile applications.
H9	Satisfaction/experience (SE) has a significant and positive impact on the perceived usefulness of mobile applications.
H10	Compatibility (COM) has a significant impact on the perceived usefulness of mobile applications.
H11	Information/awareness (IA) has a significant and positive impact on the perceived ease of use of mobile applications.
H12	Information/awareness (IA) has a significant and positive impact on the actual usage of mobile apps.

Source: Author's work

3.2.1 Data Analysis

Data was analysed and presented in two parts. The first part is assigned to descriptive analysis while the second part is assigned to Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM). Descriptive statistics were used to clearly and simply summarise the demographic information of the farmers in the study area using tables, figures, charts and graphs. This helped to achieve the first three objectives of this study, while SEM was used to analyse and present the causal relationships among the constructs in the proposed model. A two-step procedure to SEM was used. The first process was to conduct EFA and CFA, which helped to develop the measurement model and also to measure the validity of the construct instruments used in the study. The second process was to analyse the causal relationships among the constructs in the proposed model using SEM. This two-step procedure was proposed by Anderson and Gerbing (1988) and supported by Al-Jabri and Sohail (2012), Fathema (2013) and Zaremohzzabieh et al. (2015). To carry out EFA, CFA and SEM, Analysis of Moment Structure (AMOS) software and Statistical Package for the Social Science (SPSS) software were used. SEM has been chosen for this study because it can simultaneously analyse paths in the model and also test the goodness of fit of the model. The structural components of the proposed model were evaluated with SEM, using AMOS graphics.

In conducting SEM, a five step process as suggested by Lomax and Schumacker (2012) was followed:

I. Model specification

II. Model identification

III. Data preparation and screening

IV. Estimation of the model and

V. Model re-specification.

However, before conducting EFA, CFA and SEM, univariate and multivariate normality of data were tested to ensure that data generated for the study were normally distributed. Skewness and kurtosis were used to examine the univariate normality of data. A normality test was carried out because of the assumption that multivariate normally distributed data will facilitate a good result in SEM analysis (Kline, 2015). Otherwise, failure to conduct a normality test can lead to problems in the SEM analysis. According to West, Finch, and Curran (1995), the higher the level of non-normality of data, the higher the magnitude of problems being detected in SEM analysis.

3.3 Data Collection

To answer the research questions and achieve the objectives of this study, primary data were used because it enabled the researcher to collect data for the specific aim of the study (Saunders, Lewis, & Thornhill, 2009). Data were obtained from farmers in the study area (Abia State) using a structured questionnaire. A copy of the questionnaire is included in Appendix A. After evaluating different methods of data collection in addition to this study's research objectives and research methodology, a structured questionnaire was deemed appropriate, because it covers the required types of data variables, which are farmers' demographics, attitude and behaviours (Dillman, Smyth, & Christian, 2016). The succeeding subsections describe the study area, development of the survey instrument and the sampling procedures.

3.3.1 Study area

The research was conducted in Abia State, Nigeria which is located in the South-Eastern agro-ecological zones of Nigeria, with an estimated population of 3,727,300 and a total land area of about 5,834km^2 with a population density of 573.2 inhabitants/km^2 (Citypopulation, 2016). The state has predominantly low land rain forest vegetation and records a heavy annual rainfall of about 2400mm between April and October (referred to as the 'rainy season'). It is an agricultural hub in the south-east/south-south region of Nigeria and cassava, rice, and yams are the major crops grown in the state. Other crops include vegetables, maize, plantain, bananas etc. The main cash crops produced in the state include cocoa, cashews, oil palm, rubber and kola nuts. Other agricultural activities include poultry and rabbit keeping, sheep and goat rearing, pig farming and off-farm processing activities (FOS, 1999; Okezie, Sulaiman, & Nwosu, 2012). The state has three agricultural zones namely, Umuahia, Aba and Ohafia Zones as in seen in Figure 3.1.

Image removed for Copyright compliance

Figure 3.1 Abia State agricultural zones
Source:(Atoyebi, 2017)

3.3.2 Development of the Survey Instrument

With reference to the reviewed literature, a set of survey instrument was designed specifically for this study. The survey instrument comprises two parts: the first part captures demographic characteristics of the farmers while the second part captures the measured variables on eleven constructs which are presumed to have significant effects on the adoption of mobile applications by farmers. The eleven constructs are Social Influence (SI), Perceived Risk (PR), Perceived Cost (PC), Satisfaction/Experience (SE), Information/Awareness (IA), Compatibility (COM), Performance Expectancy (PE), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Intention to Use (ITU) and Actual Usage (AU). The measurement items were randomised to circumvent potential order bias.

The measurement variables on the 11 constructs were adopted from previous studies on the adoption of mobile applications (e.g. Malik et al. (2017), Lin (2011), Sharma and Mishra (2014), Al-Jabri and Sohail (2012)) and modified to suit this study. After designing the questionnaire, a pilot study was conducted on 10 randomly selected smartphone owners who either were farmers or had an interest in farming and two lecturers from the Faculty of Agribusiness and Commerce at Lincoln University, New Zealand. This helped to ascertain the reliability, validity and clarity of the questionnaire. The responses and comments obtained that were used to improve the questionnaire were necessary for clarity in meaning.

3.3.3 Sample and Procedure

Probability and non-probability sampling techniques were used to statistically estimate the characteristics of the farmers as well as determine the factors that influence the adoption of mobile phone from the study area.

A total of 261 farmers were interviewed in the three agricultural zones in Abia state (Umuahia zone, Aba zone, and Ohafia zone) using a structured questionnaire, out of which 245 were valid and useful, and 16 were rejected because they had incomplete answers. A combination of online surveys and paper questionnaires were used with the help of two research assistants whose duties were to assist the farmers where and when necessary in completing the questionnaires. The online survey was designed using Qualtrics and administered using an Android device with the guidance of the researcher and two research assistants.

A stratified random sampling technique was used in this study as farmers in the study area were stratified into three agricultural zones (strata). Within each stratum, convenience sampling technique was used to sample farmers based on their attendance to extension meeting. Convenience sampling was used due to the unavailability of sampling frame within each stratum. An average of 82 farmers who were representative of the study area was surveyed (See Table 3.2). The same fundamental questions were administered to the farmers. The sample farmers in the study area included both livestock farmers, food crop farmers, poultry farmers and fish farmers (See Table 4.5 in Chapter 4). The questionnaire focus was on three classes of mobile application which are Information/news mobile apps, productivity mobile apps and social media mobile apps.

Table 3.2 Respondents from three agricultural zones in Abia

Agri Zones	**No of respondents**	**Percentage**
Umuahia	90	37
Aba	85	34
Ohafia	70	29
Total	**245**	**100**
Average	**82**	

Source: Author's work

CHAPTER FOUR

Data Analysis - Descriptive Statistics

4.1 Introduction

This chapter presents the descriptive statistics and discussion with regard to data generated from the study area and the relevant literature review. The analysis provides simple summaries of the farmers' demographics, type of farm activities engaged in, smartphone ownership, the operating systems used and mobile applications used. The computed statistics combine the data from 245 farmers gathered from the three agricultural zones in the study area. However, at the end of this chapter, variations from the three zones will be presented. The first sets of distribution characteristics presented in Table 4.1 are the central tendency, measures of dispersion and standard errors of the mean. The central tendencies shown are mean, median and mode of the distribution. The measures of dispersion examined are variance and standard deviation, while the standard errors of the mean include measures of the amount of error to be expected because the sample mean represents the mean of repeated samples (Urdan, 2011). The inclusion of a standard deviation in the descriptive statistics is considered appropriate and supported by Dassanayake (2013, p. 20) because the mean has been calculated as a measure of the central tendency.

Table 4.1 Descriptive statistics

	N		Mean	Std. Error of Mean	Median	Mode	Std. Deviation	Variance
	Valid	Missing						
Gender	245	0	1.50	0.032	2.00	2	0.50	0.25
Age	245	0	2.78	0.044	3.00	3	0.69	0.48
Marital Status	245	0	2.03	0.039	2.00	2	0.61	0.38
Education Level	245	0	3.29	0.051	3.00	4	0.81	0.65
Family Size	245	0	2.50	0.049	3.00	3	0.77	0.59
Farm Size	240	5	0.70	0.109	0.34	0.13	1.71	2.93
Years of experience	244	1	13.34	0.710	10.00	10	11.09	122.97
Type of Farming	245	0	1.72	0.064	1.00	1	1.00	1.01
Percentage Consumed	245	0	2.36	0.068	2.00	2	1.07	1.14
Farm Meeting	245	0	2.66	0.080	3.00	3	1.25	1.57
Smart Phone ownership	245	0	1.31	0.030	1.00	1	0.47	0.22
Operating System	245	0	0.95	0.064	1.00	1	1.01	1.01
Use Apps for Farm	245	0	0.81	0.040	1.00	1	0.63	0.40

Source: Author's fieldwork (2018)

Table 4.1 above provides an overview of the data generated for this study. The results presented are mostly in their SPSS coded state which will be further analysed and interpreted for clearer understanding. As can be seen from the table above, there are a few missing data from this survey and the reason is that most of the data were collected using an online technique. The questions had forced responses, which means that a respondent cannot move to the next question if an answer has not been provided to the preceding question. However, in the case of farm size where there were five missing data, answers were provided, but the farmers did not specify if the size was in plot, acre or hectare. As a result, the answers were considered invalid. The measures used for the demographic data were either nominal or scale. For instance, the age of the farmers, family size and the percentage of produce consumed were all answered in scale while the rest were nominal where the farmers had to provide a specific answer. To analyse these data using SPSS the answers were coded. For instance, gender had two options, male or female. These two options were coded "1" for male and "2" for female. Age had four scale options, 18-25 years, 26-40 years, 41-60 years and over 61 years. The reason for using such scales was to protect the respondent's anonymity and also to avoid the problem of non-response error (Saunders et al., 2009). The answers generated were coded in SPSS 1 to 4, respectively.

The results from Table 4.1 were generated using these SPSS codes. They were carried out to have an overall statistical measure of the data generated for this study, and to ensure that the data were interpreted appropriately and that seeming relationships shown were significant and not occurrences that happened by chance (Hill, Griffiths, Lim, & Lim, 2008; Urdan, 2011).

The following sub-sections will discuss in detail the demographic characteristics and farm enterprises of the farmers and their mobile technology preferences.

4.2 Demographic Characteristics

4.2.1 Gender and Age

Out of the 245 valid responses, 49.8 percent of them reported their gender as male while 50.2 percent reported being female. The farming population in the study area seemed to be balanced between both genders. Over 52 percent of the respondents fell into the age bracket of 41-60 years, which indicates that a higher number of mature adults make up the farming population. This was closely followed by 26-40 years at 32 percent, 13.9 percent of the farmers were over 61 years, while 1.6 percentwere of ayounger age of 18-25 years (Table 4.2)

Table 4.2 Gender and age of farmers in Abia State

Variable	Description	Frequency	Percent (%)
Gender	Male	122	49
	Female	123	51
	Total	245	100
Age	18 – 25	4	2
	26 – 40	79	32
	41 – 60	128	52
	over 61	34	14
	Total	245	100

4.2.2 Marital Status and Family Size

Over 66 percent of the respondents were reported to be married, 16 percent were single, while 17 percent were widowed. Only three farmers were reported as being divorced which makes up 1.2 percent of the respondents. Family sizes of 3-5 and 6-8 persons had the highest share of the family sizes at 40 percent and 42 percent respectively. Families with 1-2 persons were nine percent while families with more than eight persons were eight percent (Table 4.3).

Table 4.3 Marital status and family size

Variable	Description	Frequency	Percent (%)
Marital status	Single	39	16
	Married	162	66
	Widowed	41	17
	Divorced	3	1
	Total	245	100
Family size	1 – 2	22	9
	3 – 5	99	40
	6 – 8	104	43
	More than 8	20	8
	Total	245	100

4.2.3 Educational Level

The study revealed that 114 (47 percent) out of 245 respondents had acquired or were in the process of acquiring tertiary education. This indicates a high literacy level among the farmers in the study area. Correspondingly, 99 respondents (40 percent) had acquired education up to secondary level, 21 (9 percent) up to primary level, and 11 farmers (5 percent) were reported to have no formal education (Table 4.4).

Table 4.4 Educational levels of farmers

Variable	Description	Frequency	Percent (%)
Educational level	No formal education	11	5
	Primary	21	9
	Secondary	99	40
	Tertiary	114	46
	Total	245	100

4.3 Farm Enterprise

4.3.1 Farm Size, Farm Type and Years of Experience

The results from the survey show that over 96 percent of the farmers from the study area were smallholders who owned or cultivated farmland of less than five hectares as seen in Table 4.5. Of all farmers, 76 percent (185 farmers) cultivated farmland of less than 1 hectare, while 21 percent (53 farmers) cultivated farmland of between one and five hectares. This is representative of FAO statistics on smallholders' average farm size in Nigeria, which is 0.53 hectares (FAO, 2018). Only two farmers reported that their farm size was above five hectares (15 and 20 hectares). They only make up less than one percent of the sampled population. Four major types of farming stood out from the survey: crop farming, livestock farming, poultry farming and fish farming. Some farmers reported having more than one farming enterprise but were asked to choose the main one. The 245 sampled farmers reported one among the listed four farm types as their main farming enterprise and 61 percent of the farmers were crop farmers, 11 percent were livestock farmers, 20 percent were poultry farmers and six percent were fish farmers. Regarding their level of experience, over 58 percent of the farmers had less than 10 years of experience. Six percent reported having over 30 years of experience, while two percent had over 41 years of experience as shown in Table 4.5

Table 4.5 Farm size, farm type and years of experience

Variable	Description	Frequency	Percent (%)
Farm size	less than 1 hectare	185	75
	1- 5 hectares	53	22
	More than 5 hectares	2	1
	Missing	5	2
	Total	245	100
Farm type	Crop farming	150	61
	Livestock	29	12
	Poultry	50	20
	Fishery	16	7
	Total	245	100
Years of experience	1-10	144	59
	11-20	52	21
	21-30	27	11
	31-40	15	6
	41 and above	6	2
	Missing	1	0.4

	Total	245	100

4.3.2 Extension Meeting Attendance and Level of Produce Consumed

Based on how data was collected for this study, it was expected that most of the farmers would report having attended an extension meeting because they were surveyed during this meeting. As seen in Table 4.6, 89 percent of the farmers do attend extension meetings, though at varying degrees. But 31 percent reported that they attend the meetings sometimes. However, 11 percent that reported "Never" to meeting attendance were randomly selected and surveyed individually from the study area. Regarding the farmers' level of commercialisation, they were asked the amount of their produce that they consume themselves, in order to ascertain that they were not all subsistence farmers. Less than three percent reported that they consume 81 to 100 percent of their entire produce. Although studies (Baiphethi & Jacobs, 2009; Sibhatu & Qaim, 2017) have shown that subsistence farmers do contribute to food security and economic growth in developing countries, this makes the 2.4 percent of farmers who reported that they consume 81 to 100 percent of their produce an important group in the sampled population. Over 50 percent of the farmers combined consume less than 25 percent of their produce, which indicates a high level of commercialisation as the remaining 75 percent were sold in the market (Table 4.6).

Table 4.6 Extension meeting and level of produce consumed

Variable	Description	Frequency	Percent (%)
Farm meeting	Always	53	22
	Most of the time	61	25
	Sometimes	76	31
	Rarely	27	11
	Never	28	11
	Total	245	100
Amount of produce consumed	less than 10%	61	25
	11 - 25%	80	33
	26 - 50%	66	27
	51 - 80%	32	13
	81 - 100%	6	2
	Total	245	100

4.4 Mobile Technology Preferences

4.4.1 Smartphone Ownership, Operating System and Mobile App Use for Farm Activities

Over 68 percent of the farmers reported “Yes” to smartphone ownership. The remaining 32 percent had low-end mobile phones. Those 168 farmers who use smartphones went on to reveal the operating systems on their smartphone. This is very important to note, as it determines the kind of mobile application that could be installed on such smartphones (Divya & Kumar, 2016). The Android operating system appeared to be the most used mobile operating system with 83 percent of the smartphone users affirming its usage (Table 4.7). Ten percent use the Blackberry operating system while four percent use iOS. Windows appeared to be the least used with a three percent share as shown in Figure 4.1. The bottom half of Table 4.7 shows the number of farmers who use mobile apps for their farm activities. 138 farmers (82 percent) confirmed that they use mobile applications for their farm activities while 30 farmers (18 percent) have a smartphone but use it for other purposes. To sum up, out of 245 farmers surveyed, 168 have a smartphone and 138 use their smartphones for farm activities. The next section reveals the apps they use and the level of use

Table 4.7 Smartphone ownership, operating system and apps usage

Variable	Description	Frequency	Percent (%)
Smartphone Ownership	Yes	168	69
	No	77	31
	Total	245	100
Operating system used	Android	140	83
	iOS	7	4
	Windows	5	3
	Blackberry	16	10
	Total	168	100
Mobile app use for farm activities	Yes	138	82
	No	30	17
	Total	168	100

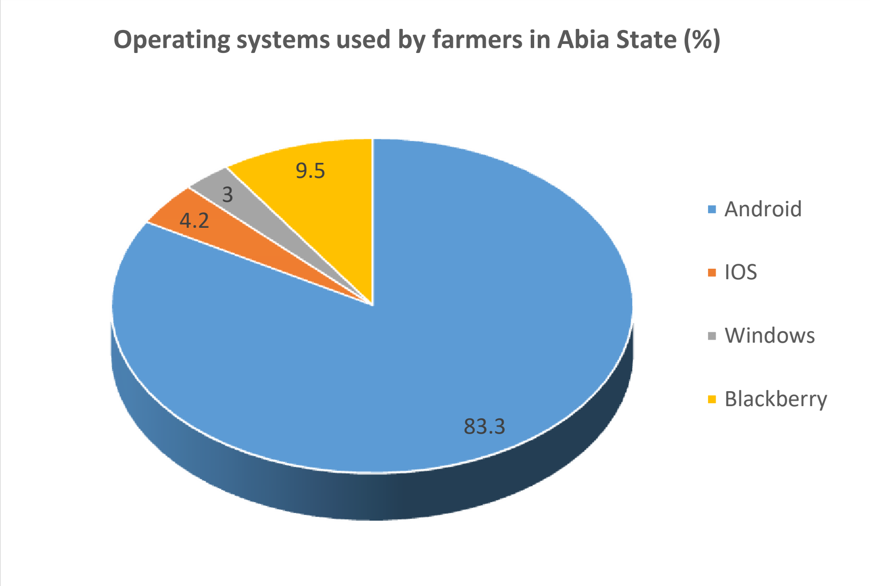

Figure 4.1 Mobile operating systems used by farmers in Abia state. (%)

4.4.2 Mobile Applications Used by Farmers.

Table 4.8 presents the summary of all mobile applications used by farmers in Abia State. A total of 12 mobile applications were reported. For each mobile app, the number of users and the usage level differed among farmers. As shown in Figure 4.2, WhatsApp emerged as the most used mobile app followed closely by a mobile banking app and compare-the-market with 125, 111 and 77 users respectively. The three distinct classifications of mobile apps made the top of the list on most used mobile apps: WhatsApp for a social media app, Mobile Banking App for a productivity mobile app and Compare-the-market for an information mobile app. Hello Tractor and Instagram were the least used by the farmers (Figure 4.2).

Table 4.8 Mobile apps used by farmers in Abia State

Nos	Mobile Applications	No of Users
1	Probity Farm	37
2	Compare-the-Market	77
3	FarmCrowdy	11
4	Hello Tractor	6
5	AgroData	56
6	WhatsApp	125
7	Telegram	38
8	Cellulant	7
9	GES E-Wallet	45
10	Mobile banking App	111
11	Facebook	11
12	Instagram	1

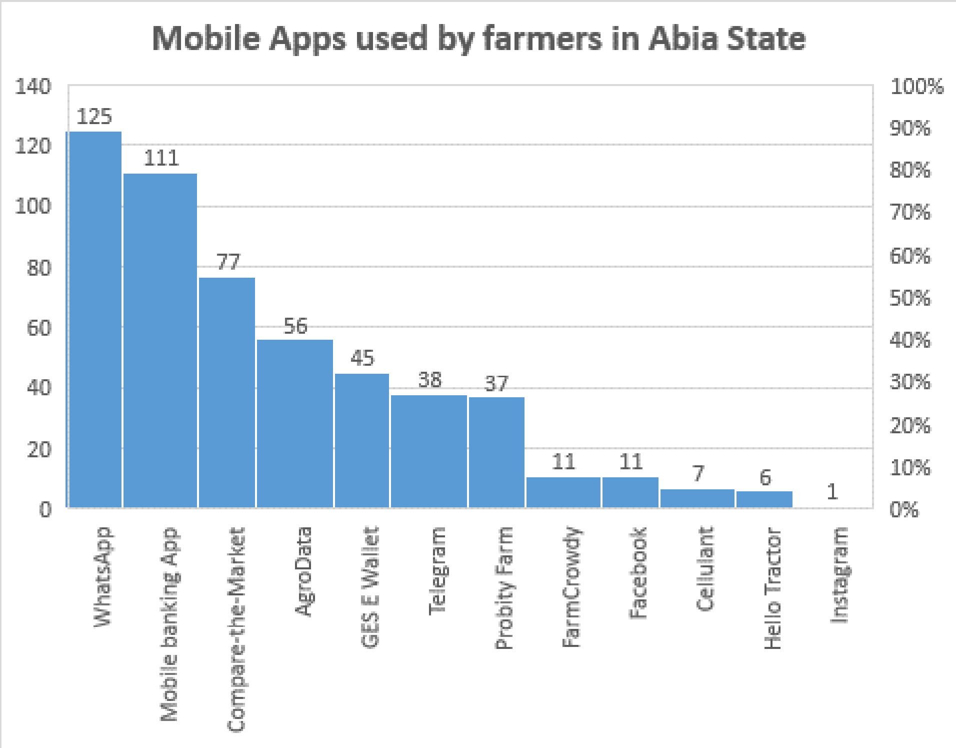

Figure 4.2 Mobile apps used by farmers in Abia State.

4.4.3 Mobile Application Level of Usage

Table 4.9 and Figure 4.3 provide the summary statistics for the level of usage of the mobile applications used by farmers in Abia state. WhatsApp has the highest number of frequent users (97 users). Mobile Banking Apps followed closely with 72 frequent users, while Cellulant, Hello Tractor and Instagram have the least number of frequent users (Figure 4.3). Some of the applications listed by the farmers can be used for other purposes. However, for the purpose of this study, farmers were asked to include such an application only if they use it for their farming business. Examples of such applications include WhatsApp, Mobile Banking Apps, Telegram, Facebook, and Instagram.

Table 4.9 Mobile applications level of usage

	Level of Usage				
Mobile Apps	**Always**	**Most of the time**	**Sometimes**	**Rarely**	**Total**
WhatsApp	48	49	28		125
Mobile Banking App	32	40	38	1	111
Compare-the-market	17	38	21	1	77
AgroData	13	30	13		56
GES E-Wallet	7	12	26		45
Telegram	10	13	15		38
Probity Farm	4	15	17	1	37
FarmCrowdy	2	3	5	1	11
Facebook	5	1	5		11
Cellulant		1	6		7

Hello Tractor		3	3		6
Instagram		1			1

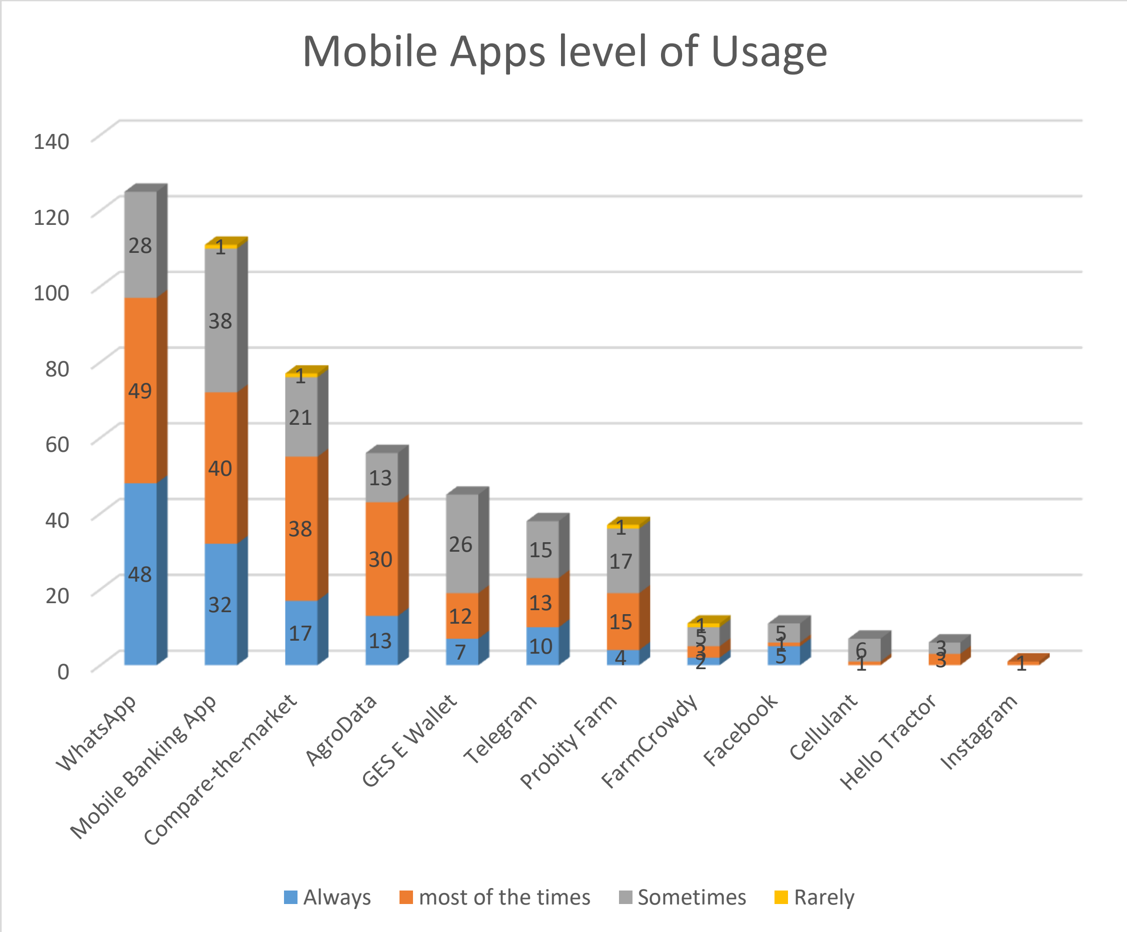

Figure 4.3 Mobile apps level of usage

4.5. Relationships between Demographic Variables, Smartphone Ownership and Usage for Farming Activities.

4.5.1 Gender

Figure 4.4 depicts the level of smartphone ownership and usage, according to gender. Despite the small difference, male farmers appear to own more smartphones and also use mobile apps in their farming activities more than the female ones. As referred to previously in Table 4.2, female farmers outnumber the male farmers in the study area, with 51 percent against 49 percent, but the male farmers own and use more apps than the female farmers. This result is consistent with a study by Rachel (2016), which showed that Kenyan women were less likely to use their smartphones for a variety of tasks than the men. Similarly, Evans, Hopper, Knezek, and Jones (2013) found in their study that gender was a significant predictive variable in smartphone usage.

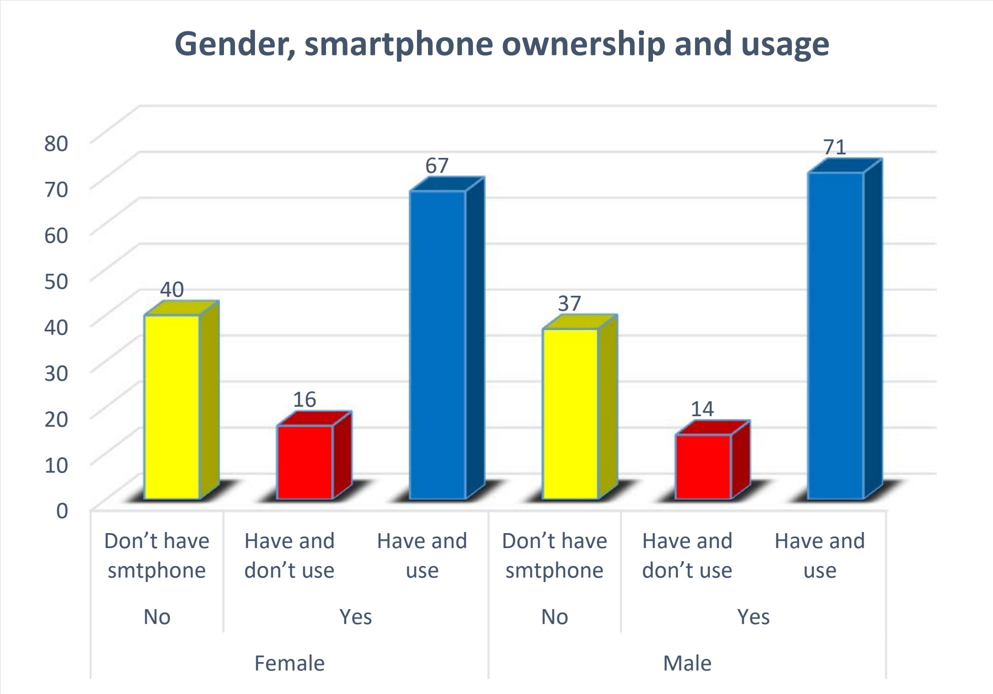

Figure 4.4 Gender, smartphone ownership and usage

4.5.2. Age

Figure 4.5 shows the effect of age on smartphone ownership and usage. Age was grouped into four categories (see Table 4.2). The second and the third groups (26-40 and 41-60 years) owned the most smartphones and used mobile apps for their farming activities. According to Dimock (2018), both groups fall under the generation known as "Millennials or Gen Y" and "Generation X". Similar research on smartphone ownership and usage by Poushter (2016) and Jiang (2018), found that more than nine-in-ten Millennials owned and used smartphone applications in both advanced economies and emerging and developing nations. This study confirmed their findings. Six out of every seven Millennials had a smartphone and three out of every four smartphone owners used mobile applications in their farming activities (See Figure 4.5).

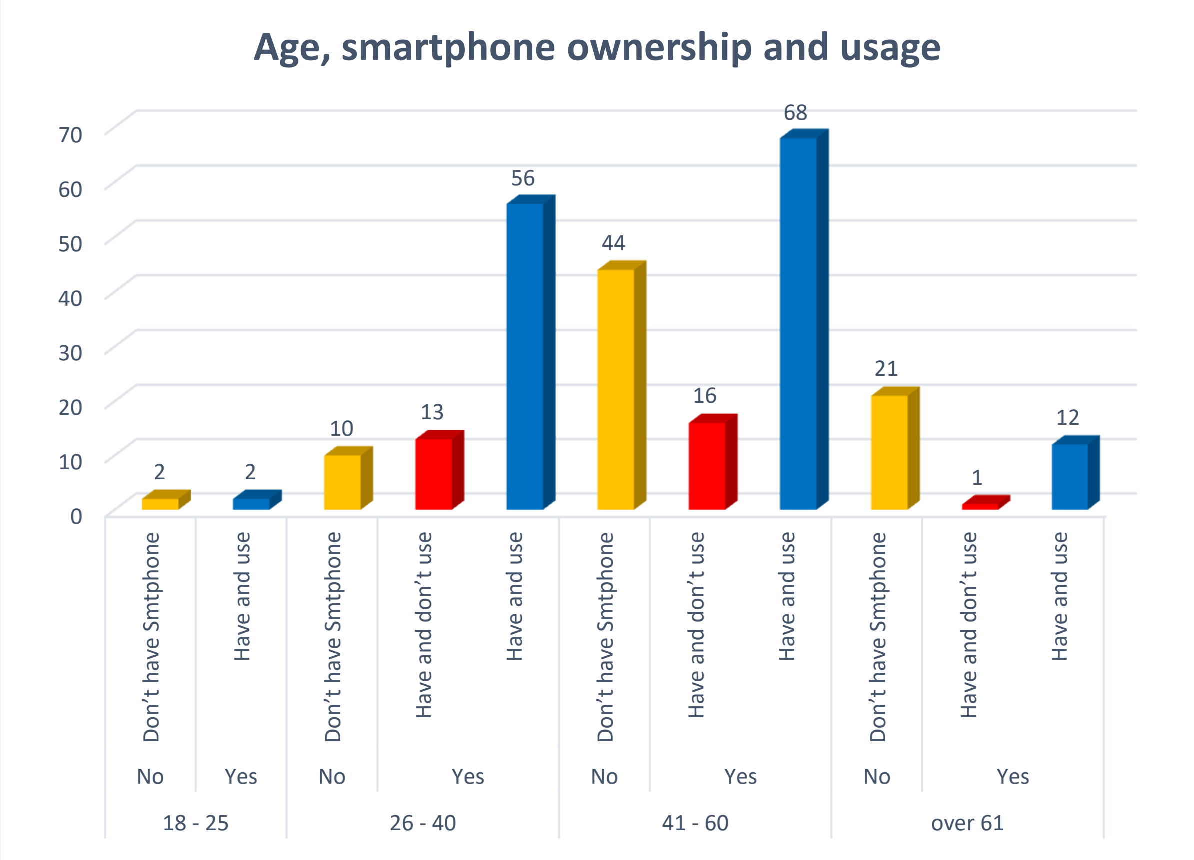

Figure 4.5 Age, smartphone ownership and usage

4.5.3 Educational Level

Education had the greatest impact amongst the demographic variables (Figure 4.6). It appeared that the higher a person's level of education, the higher the likelihood they owned and used mobile apps for their farm activities. More than 90 percent of those with no formal education and primary education had no smartphone, while over 90 percent of those with tertiary education owned a smartphone. Eighty-five percent of those who own smartphones used mobile apps for their farm activities (Figure 4.6). This is in line with findings by Poushter (2016, p. 19) on smartphone ownership and internet usage, where he found that "those with more education are more likely to own a smartphone and use the internet than those with less education".

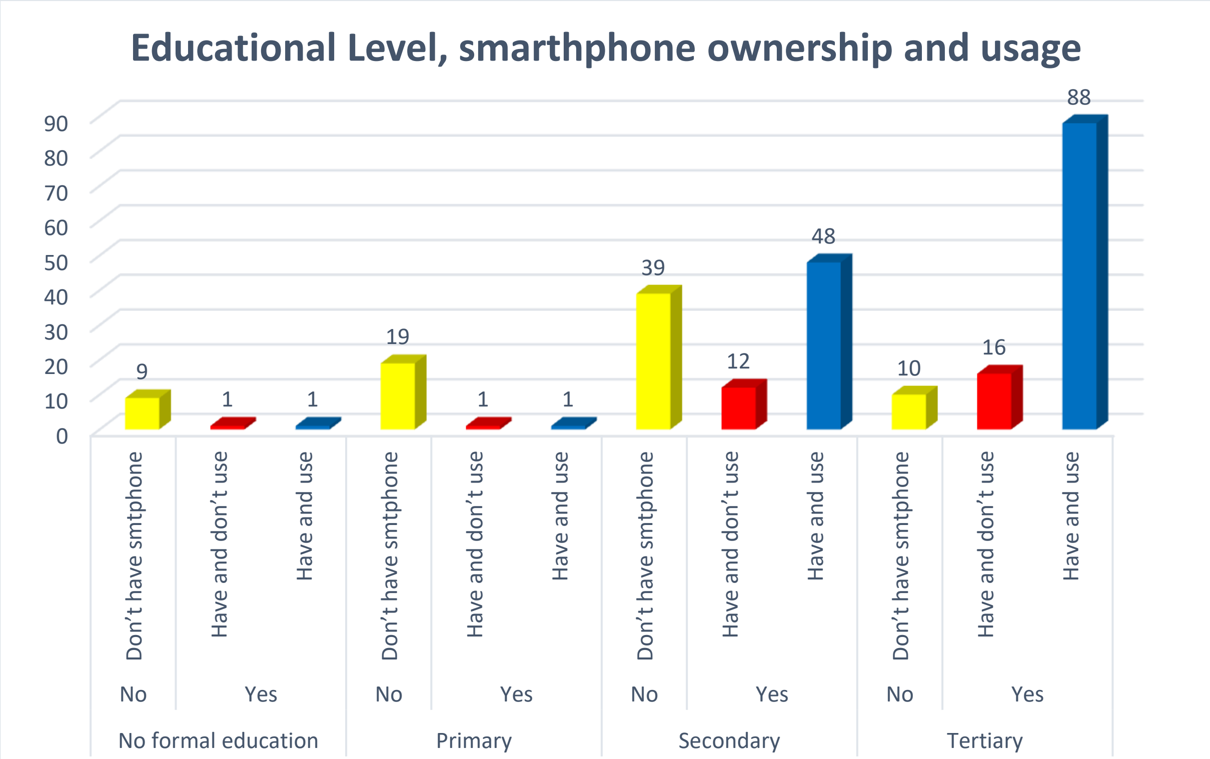

Figure 4.6 Education, smartphone ownership and usage

4.6 Farmers’ Interest in and Willingness to Use Mobile Applications

The interest and willingness of farmers to use mobile phone applications in their daily farming activities were assessed using some of their responses from the survey. Descriptive statistics were used to analyse their response to these questions. A total of seven questions asked under the constructs: Perceived Usefulness (PU) and Intention to Use (ITU). PU and ITU mobile applications, helped to achieve this purpose.

4.6.1 Perceived Usefulness (PU)

As seen in Table 4.10, four questions were asked regarding how farmers perceived the usefulness of mobile applications. Over 70 percent positive responses were recorded in each of the four questions. This is an indication that farmers perceived mobile applications to be useful. After having ascertained their perception, the next few questions on the constructs, ITU and Social Influence (SI), will help validate their interest in and willingness to use mobile applications.

Table 4.10 Farmers' responses to questions regarding how they perceive mobile apps

Question	**Response**	**Frequency**	**Percent (%)**
"Using mobile applications can improve my productivity."	Strongly agree	18	7
	Agree	87	36
	Somewhat agree	91	37
	Somewhat disagree	21	9
	Disagree	15	6
	Strongly disagree	13	5
	Total	245	100
"Using mobile applications can improve my income."	Strongly agree	16	7
	Agree	79	32
	Somewhat agree	88	36
	Somewhat disagree	38	16
	Disagree	17	7
	Strongly disagree	7	3
	Total	245	100
"Using mobile applications can help me make and receive payments faster (farm business)."	Strongly agree	28	11
	Agree	100	41
	Somewhat agree	67	27
	Somewhat disagree	21	9
	Disagree	15	6
	Strongly disagree	14	6
	Total	245	100
"Using mobile applications will help me locate markets and sell my produce."	Strongly agree	30	12
	Agree	81	33
	Somewhat agree	69	28
	Somewhat disagree	31	13
	Disagree	21	9
	Strongly disagree	13	5
	Total	168	100

4.6.2 Intention to Use (ITU)

Three questions captured farmers' intention to use mobile apps as seen in Table 4.11. Similarly, to farmers' PU of mobile apps, their responses to questions on their intention to use mobile apps were over 70 percent positive in all questions. This shows a high indication of interest and willingness to use mobile applications.

Table 4.11 Farmers' responses to questions regarding their intention to use mobile apps

Question	Response	Frequency	Percent (%)
"Given that I have access to mobile apps, I predict that I will use agricultural mobile apps in the future."	Strongly agree	39	16
	Agree	102	42
	Somewhat agree	68	28
	Somewhat disagree	19	8
	Disagree	8	3
	Strongly disagree	9	3
	Total	245	100
"I am very enthusiastic about agricultural mobile applications."	Strongly agree	17	7
	Agree	78	32
	Somewhat agree	62	25
	Somewhat disagree	44	18
	Disagree	26	11
	Strongly disagree	18	7
	Total	245	100
"I encourage other farmers to use mobile applications."	Strongly agree	44	18
	Agree	84	34
	Somewhat agree	70	29
	Somewhat disagree	26	11
	Disagree	15	6
	Strongly disagree	6	2
	Total	245	100

4.6.3 Social Influence (SI)

Three questions were asked to determine the impact of SI on farmers' willingness to use mobile applications. Unlike the responses from PU and ITU constructs, where over 70 percent positive responses were recorded, only over 50 percent positive responses were recorded in all the questions capturing the impact of SI (Table 4.12). Although SI may not have a dominant impact on farmers' willingness and interest to use mobile apps, an over 50 percent positive response is an indication that farmers are willing to use mobile applications. The impact of SI on actual usage of mobile apps will be explored in the next chapter using Structural Equation Modelling (SEM).

Table 4.12 Farmers’ responses to questions about Social Influence.

Question	Response	Frequency	Percent (%)
“I am more likely to use agricultural mobil apps because other farmers are usin them”	Strongly agree	9	4
	Agree	63	26
	Somewhat agree	67	27
	Somewhat disagree	49	20
	Disagree	30	12
	Strongly disagree	27	11
	Total	245	100
“I am more likely to use mobile app because people who are important to m think I should use them”	Strongly agree	10	4
	Agree	66	27
	Somewhat agree	49	20
	Somewhat disagree	44	18
	Disagree	47	19
	Strongly disagree	29	11
	Total	245	100
“I am more likely to use mobile app because the extension officer recommende mobile apps to all farmers”	Strongly agree	6	2
	Agree	67	27
	Somewhat agree	77	34
	Somewhat disagree	42	17
	Disagree	37	15
	Strongly disagree	16	7
	Total	245	100

4.7 Summary

The descriptive statistics results presented in this chapter addressed research questions one, two, three and four. Descriptive statistics were used to clearly and simply summarize the demographic information of the farmers in the study area such as age, gender, educational level and farm enterprise. In addition to the farmers’ demographic information, the analysis revealed the type of phones and operating system on the phones used by farmers, the applications being used by farmers in the study area, the factors that distinguish farmers that use mobile applications from those that do not use mobile apps and the level of interest in and willingness of the farmers to use mobile applications in their daily farming activities.

Unlike previous studies on the use of mobile phone by farmers (Asa & Uwem, 2017; Ogunniyi & Ojebuyi, 2016), this study differentiated between the phones used by farmers in the study area, where 69 percent of the farmers use smartphones while 31 percent use low-end mobile phones. Age and level of education were found to be distinguishing characteristics on the type of phone used by farmers and their usage of mobile applications in their farm activities. The Millennials and Generation X mostly used smartphones and mobile applications in their farming activities when compared to other generations. As the educational level of the farmers increased, the higher the chances of their using smartphones and mobile apps.

The farmers were using four main operating systems. The Android operating system was the most used with 83 percent of the farmers making use of it. Twelve mobile applications were discovered to be in use in the study area. WhatsApp, Mobile Banking App and AgroData were the most used mobile applications by the farmers. The next chapter will analyse and discuss the factors that affect their use of mobile applications in their farming activities.

CHAPTER FIVE

Data Analysis: Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM)

5.1 Introduction

This chapter presents the empirical analysis on factors that influence the adoption of mobile phone applications by farmers in the study area using Structural Equation Modelling (SEM). SEM was used to analyse and present the causal relationships among the constructs in the proposed model (Extended Technology Acceptance Model (TAM2)). A two-step procedure to SEM was used. The first process was to conduct Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), which helped to develop the measurement model. It also helped to measure the validity of the construct instruments used in the study. The second process was to analyse the causal relationships among the constructs in the proposed model using SEM.

5.2 Data Screening and Normality test

Before conducting CFA and SEM, case and variable screening were carried out to ensure that there was no missing data, and that the respondents were well engaged while taking the survey. However, no missing data were recorded in SEM measurement variables because the survey software used in the data collection prevented incomplete responses. Exceptionally, the last part of the questionnaire had two constructs with seven measurement variables that were meant for farmers who used mobile applications only. Farmers that did not use mobile apps were made to ignore these questions because the questions did not apply to them and so they were coded in SPSS as Zero (0) which represented "not applicable" rather than missing data.

The normality test showed a relatively small variation from a normal distribution. The skewness of data ranged from -0.02 to 1.41, while kurtosis of the data ranged from -0.045 to 2.0 (Table 5.1). Fabrigar, Wegener, MacCallum, and Strahan (1999) criterion suggests that skewness and kurtosis should not be greater than two and seven respectively. Whereas Kline (2015) maintained that a skewness index greater than three is considered extremely skewed and a kurtosis index greater than 10 suggests a problem. Both skewness and kurtosis did not exceed three and 10 (Table 5.1). Based on Kline (2015) and Fabrigar et al. (1999) threshold level, the data were considered to be univariately normally distributed.

Table 5.1 Normality of data assessment

	N Valid	Missing	Skewness	Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis
InfoAware_1	245	0	0.383	0.156	-1.072	0.31
InfoAware_2	245	0	0.776	0.156	-0.15	0.31
InfoAware_3	245	0	0.516	0.156	-0.455	0.31
InfoAware_4	245	0	0.893	0.156	0.235	0.31
Compat_1	245	0	0.577	0.156	-0.983	0.31
Compat_2	245	0	0.295	0.156	-1.023	0.31
Compat_3	245	0	0.531	0.156	-0.732	0.31
InterConn_1	245	0	0.643	0.156	-0.762	0.31
InterConn_2	245	0	0.264	0.156	-1.103	0.31
InterConn_3	245	0	-0.404	0.156	-1.114	0.31
PriCost_1	245	0	0.652	0.156	-0.606	0.31
PriCost_2	245	0	0.254	0.156	-1.031	0.31
PriCost_3	245	0	-0.188	0.156	-0.742	0.31
PriCost_4	245	0	0.698	0.156	-0.47	0.31
SocInflu_1	245	0	0.387	0.156	-0.781	0.31
SocInflu_2	245	0	0.169	0.156	-1.14	0.31
SocInflu_3	245	0	0.467	0.156	-0.671	0.31
RiskAver_1	245	0	0.115	0.156	-0.943	0.31
RiskAver_2	245	0	-0.02	0.156	-0.701	0.31
RiskAver_3	245	0	-0.154	0.156	-0.749	0.31
RiskAver_4	245	0	0.305	0.156	-0.379	0.31
PerfExp_1	245	0	0.695	0.156	-0.045	0.31
PerfExp_2	245	0	1.406	0.156	2.004	0.31
PerfExp_3	245	0	0.532	0.156	-0.144	0.31
PerfExp_4	245	0	0.507	0.156	-0.584	0.31
PercEOUse_1	245	0	0.599	0.156	-0.69	0.31
PercEOUse_2	245	0	0.647	0.156	0.08	0.31
PercEOUse_3	245	0	0.59	0.156	0.011	0.31
PercEOUse_4	245	0	0.436	0.156	-0.428	0.31
PercUsfness_1	245	0	0.961	0.156	0.722	0.31
PercUsfness_2	245	0	0.646	0.156	0.248	0.31
PercUsfness_3	245	0	0.993	0.156	0.518	0.31
PercUsfness_4	245	0	0.676	0.156	-0.156	0.31
IntenToUse_1	245	0	1.09	0.156	1.324	0.31
IntenToUse_2	245	0	0.517	0.156	-0.558	0.31
IntenToUse_3	245	0	0.737	0.156	0.229	0.31
ActualUsage_1	245	0	1.16	0.156	1.32	0.31
ActualUsage_2	245	0	0.748	0.156	0.028	0.31
ActualUsage_3	245	0	0.678	0.156	-0.457	0.31

ActualUsage_4	245	0	0.721	0.156	-0.53	0.31
SatisExp_1	245	0	0.172	0.156	-1.689	0.31
SatisExp_2	245	0	0.814	0.156	0.33	0.31
SatisExp_3	245	0	0.42	0.156	-1.197	0.31

5.3 Exploratory Factor Analysis (EFA)

EFA is a statistical method that tries to uncover complex patterns by exploring the dataset and testing predictions (Yong & Pearce, 2013). EFA was carried out to define the underlying structure among the variables in the measurement model. It helped to identify the correlation patterns among the measurement variables and to reduce them to latent factors based on the underlying structure of the data (Yong & Pearce, 2013). The EFA analysis was carried out using IBM® SPSS® software using Principal Component Analysis (PCA) with an Oblique rotation method. In conducting EFA, only the reflective latent factors (Multi-indicator variables) that measure the constructs were included in the EFA (Hair, Black, Babin, & Anderson, 2010). The measurement variables were allowed to freely load onto the latent constructs and cross load onto multiple constructs based on how they correlate with each other. In the course of factor extraction on SPSS, Principal Components Method was used because, first, it has the ability to produce unique factor scores as well as avoid the problem of indeterminacy[2] (DiStefano, Zhu, & Mindrila, 2009; Grice, 2001; Hair et al., 2010); secondly, PCA takes into consideration the total variance and it also derives factors that contain small portions of unique variance (Hair et al., 2010, p. 107). To improve the interpretability of factors, Promax, an oblique rotation technique was applied because it allowed the factors that were created to be correlated (Urdan, 2011). According to Williams, Onsman, and Brown (2010, p. 9), the freedom to allow measurement items to correlate freely through oblique rotation produces more accurate results for researches involving human behaviours. Promax raises the loadings to a power of four, thereby producing superior correlations among the factors (Yong & Pearce, 2013, p. 84).

The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were added in the factor analysis to ensure that the extracted factors were appropriate and reliable (Field,

[2] The problem of indeterminacy arises when the parameters under a common factor model are not distinctively defined because of the researcher’s choice of commonality estimates.

2005). The KMO measure of sampling adequacy gave a result of 0.914 with Bartlett's test of sphericity highly significant at ($p < 0.001$) (Table 5.2). This indicates that factor analysis is appropriate (Field, 2005). According to Kaiser (1974), a sampling adequacy result close to one or greater than 0.9 is superb and it indicates that the patterns of correlations are relatively compact which shows that the factor analysis should yield reliable factors.

Table 5.2 KMO and Barlett's test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.914
Bartlett's Test of Sphericity	Approx. Chi-Square	7010.369
	Df	465
	Sig.	0.000

In factor extraction, SPSS identified 43 linear components within the data set. Eight of these components had eigenvalues greater than one, which explained a relatively large amount of variance (Hair et al., 2010; Kaiser, 1974). The total variance explained for the eight factors stood at 66.3 percent, which was above the 60 percent threshold considered as satisfactory by Hair et al. (2010).

As stated earlier, the measurement variables were allowed to freely load onto the latent constructs and cross-load into multiple constructs to reduce measurement error (Hair et al., 2010). Hair et al. (p.94) noted that in factor analysis, researchers should accept what the data present and not to set any prior constraints on the estimation of components to be extracted. Specifically, EFA explores the data set and provides the researcher with information about the number of factors that are needed to best represent the data. In other words, EFA is actually conducted without knowing the number of factors that really existed in a data set or which variable belongs with which constructs. This was evidenced in the pattern matrix where Intention to Use (ITU) and Perceived Ease of Use (PEOU) cross-loaded on one factor, explaining users' positive attitude towards mobile phone applications. Performance Expectancy (PE) and Perceived Usefulness (PU) cross-loaded as one factor explaining users' perception towards the usefulness of mobile applications, while Satisfaction/Experience (SE) cross-loaded with Actual Usage (AU) as one factor explaining users' experience with mobile phone applications. The questions defining these constructs were understood and interpreted similarly by the correspondents. This led to the high correlation of these constructs in EFA, making it difficult to separate them into distinct factors, and as a result, they were specified as three rather than six factors (Hair et al., 2010).

However, there were still minor issues of discriminant validity, which were resolved by eliminating measurement variables that loaded on multiple constructs. Williams et al. (2010) contend that measurement items that loaded on several factors do not conceptually fit the proposed logical factor structure and therefore should be discarded. This led to the removal of the Compatibility (COM) construct because the measurement items could not load on a single factor. The several factors the COM indicators loaded onto were not conceptually fit to be interpreted by these COM indicators. This brought down the extracted factors to seven with a satisfactory 77.23 percent of total variance explained, as seen in Table 5.3. To further strengthen the validity of the constructs, measurement variables with factor loading[3] less than 0.50 were deleted as suggested by Hair et al. (2010) (Table 5.4). All the factors had at least three variables with Intention to Use having five loadings while Perceived Usefulness and Actual Usage had six and seven variables loading onto each respectively. According to Tabachnick and Fidell (2007), for a construct to be labelled a factor in EFA, it should have at least three variables. They went on to say that this can be altered depending on the design of the study but suggest interpreting such with caution. In a situation where there are two variables factor, Yong and Pearce (2013, p. 80) asserted that the variables have to be highly correlated with each other and fairly uncorrelated with other variables with an $r > .70$. Considering the issue of cross-loading experienced in the EFA, Hair et al. (2010, p. 119) recommends that the factor model should be re-specified if the cross-loaded items cannot be deleted as a result of its importance to the study's objective. They further advised that the re-specification of the model should be done with respect to the conceptual foundation underlying the study. Figure 5.2 shows the re-specified model and Table 5.7 shows their corresponding hypotheses.

[3]Factor loading is a measure of how much the variables contribute to the factor. A high factor score indicates that the scopes of the factor are well interpreted by the variables (Yong & Pearce, 2013)

Table 5.3 Total variance explained

Factor number	Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	12.25	39.51	39.51
2	3.16	10.18	49.69
3	3.11	10.02	59.71
4	1.94	6.26	65.97
5	1.27	4.09	70.06
6	1.21	3.89	73.95
7	1.02	3.28	77.23

Extraction Method: Principal Component Analysis

To evaluate the internal consistency of the measurement model, a reliability test was estimated on the extracted variables as a whole and on the variable sub-set that make up the extracted factors. The Cronbach's alpha for the overall reliability showed 0.93 as seen in Table 5.5. The composite reliability for all the constructs (extracted factors) showed a satisfactory result ranging from 0.97 to 0.72, as seen in Table 5.6. Both the measurement scale and the individual constructs had a Cronbach's alpha greater than the generally agreed limit of 0.70 (Hair et al., 2010, p. 125). Hair et al. emphasised paying attention to the number of items in a scale, as a higher number of items in a scale with the same degree of inter-correlation will increase the reliability value. However, the extracted factors with the least number of variables (three items) as suggested by Tabachnick and Fidell (2007) gave a reliability score above 0.721, as seen in Table 5. 6. This indicates a good level of internal consistency in the variable set.

Table 5.4 Pattern matrix

Pattern Matrix							
	Component						
Variables	1	2	3	4	5	6	7
AU_2	0.95						
SE_2	0.94						
AU_1	0.91						
AU_3	0.91						
AU_4	0.90						
SE_3	0.89						
SE_1	0.88						
PU_1		0.97					
PE_1		0.95					
PE_2		0.77					
PU_2		0.75					
PE_4		0.74					
PE_3		0.72					
PEOU_3			0.96				
ITU_2			0.85				
PEOU_2			0.61				
ITU_1			0.60				
PEOU_4			0.54				
IA_2				0.93			
IA_4				0.90			
IA_3				0.88			
IA_1				0.67			
PR_4					0.86		
PR_2					0.84		
PR_3					0.84		
SI_2						0.82	
SI_3						0.80	
SI_1						0.66	
PC_1							0.84
PC_4							0.80
PC_2							0.70

Extraction Method: Principal Component Analysis
Rotation Method: Promax with Kaiser Normalization
Rotation converged in seven iterations.

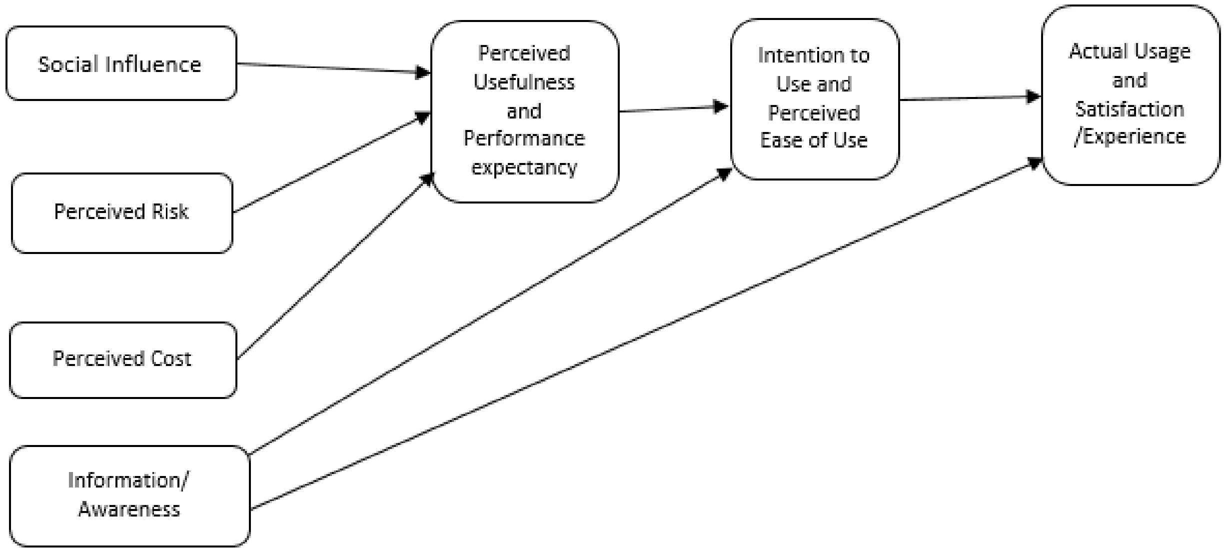

Figure 5.1 Research model based on pattern matrix

Table 5.5 Reliability of total questions

Reliability Statistics		
Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0.936	0.93	31

Table 5.6 Extracted factors, measurement variables and their Cronbach's Alpha

Constructs and Measures	Factor Loading	Cronbach's Alpha	Composite reliability (CR)
1. Actual Usage			
AU_2	0.95	0.97	0.97
SE_2	0.94		
AU_1	0.91		
AU_3	0.91		
AU_4	0.90		
SE_3	0.89		
SE_1	0.88		
2. Perceived Usefulness			
PU_1	0.97	0.92	0.92
PE_1	0.95		
PE_2	0.77		
PU_2	0.75		
PE_4	0.74		
PE_3	0.72		
3. Intention to Use			
PEOU_3	0.96	0.87	0.87
ITU_2	0.85		
PEOU_2	0.61		
ITU_1	0.60		
PEOU_4	0.54		
4. Information/Awareness			
IA_2	0.93	0.92	0.92
IA_4	0.90		
IA_3	0.88		
IA_1	0.67		
5. Perceived Risk			
RA_4	0.86	0.82	0.82
RA_2	0.84		
RA_3	0.84		
6. Social Influence			
SI_2	0.82	0.73	0.73
SI_3	0.80		
SI_1	0.66		
7. Perceived Cost			
PC_1	0.84	0.72	0.72
PC_4	0.80		
PC_2	0.70		

Extraction Method: Principal Component Analysis.
Rotation Method: Promax with Kaiser Normalization.
Rotation converged in seven iterations.

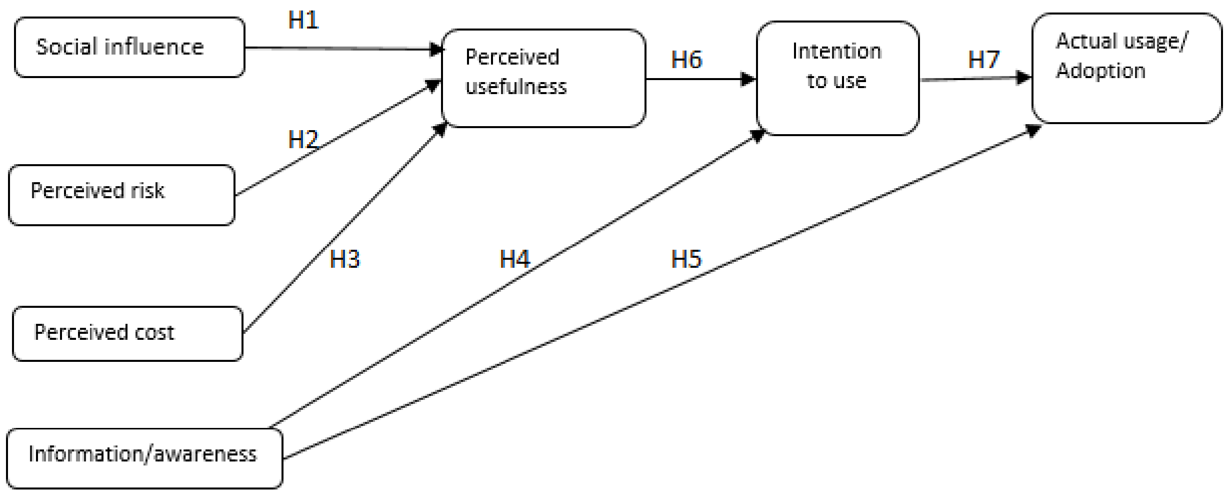

Figure 5.2 Re-specified research model

Table 5.7 Re-specified hypotheses

	Hypotheses
H1	SI has a significant and positive impact on the perceived usefulness of mobile applications.
H2	PR has a significant and negative impact on the perceived usefulness of mobile applications.
H3	PC has a significant and negative impact on the perceived usefulness of mobile applications.
H4	IA has a significant and positive impact on farmers' intention to use mobile applications
H5	IA has a significant and positive impact on the actual usage of mobile apps
H6	PU has a significant and positive impact on farmers' intention to use mobile applications.
H7	ITU has a significant and positive effect on the actual usage of mobile apps

5.4 Confirmatory Factor Analysis (CFA)

CFA was used to validate the factorial validity of the model derived from EFA. It helped to ensure that the measured variables represent the constructs in the model (Fathema, 2013; Hair et al., 2010). The CFA analysis was carried out using IBM® AMOS® software version 25. In conducting the CFA, the 31 measurement items extracted from EFA were allowed to load only on their specific factors thereby generating a CFA model. The model presented the covariance between the latent factors. This enabled the testing of goodness-of-fit of the factors in the measurement model. It also facilitated the calculation of convergent validity, discriminant validity and composite reliability score. From the CFA model, a correlation assessment was carried out between the measurement items on each construct to ascertain that none of the items had a factor loading below 0.50. As suggested by Hair et al. (2010), measurement items in the CFA model that are below 0.50 should be considered for deletion to improve the validity of the constructs. The items in the model showed a strong correlation as they were all above 0.50 as seen in Figure 5.3.

Based on the outcome of EFA shown in Table 5.4, the revised model of seven factors (constructs) with 31 measurement items (variables) is presented below in Figure 5.3.

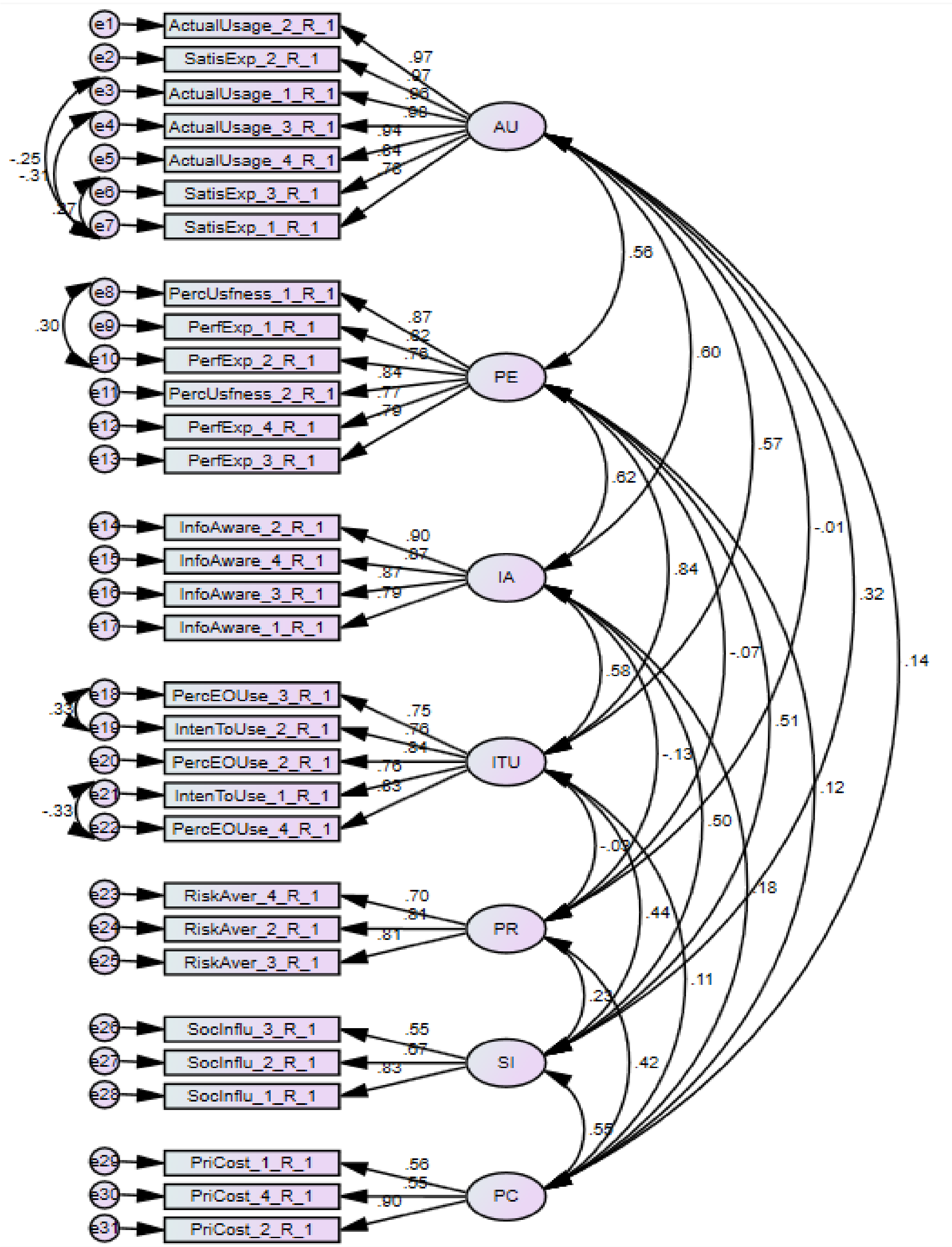

Figure 5.3 Seven factor CFA model with standardized estimates

The measurement model (Figure 5.3) depicts how the constructs and measurement items relate to each other. The constructs are represented in oval shapes while the measurement items are represented in rectangular shapes. The seven constructs are allowed to correlate with each other while the measured items are allowed to load only on the construct they measure. The error terms (e) are allowed to relate to one measured item each. The causal relationship between a construct and measurement items is represented by a one-headed arrow, while the covariance between the constructs is represented by two-headed arrows. The error terms are correlated to each other within the set of measurement items, interpreting a construct, because the result of the modification indices from CFA suggests that they share the same conceptual basis, and empirically, they tend to move together. In essence, there is a strong similarity between the measurement items (Hair et al., 2010, p. 718). This further helped to strengthen the model fit of the measurement model.

5.4.1 Testing of Measurement Model Validity

The measurement model was tested for model fit and validity measures, such as construct validity, construct reliability, convergent validity, and discriminant validity. These tests helped to prove that the measurement model is satisfactorily adequate for subsequent Structural Equation Modelling. To successfully assess a measurement model, Hair et al. (2010) suggest three key measures: the first is to examine the CFA model to ensure that the least loading should not be less than 0.5, and if any loading is less than 0.5, it should be considered for deletion. Secondly, the statistical significance of each estimated coefficient should be assessed, and non-significant estimates suggest that an item should be dropped. Finally, the model fit should be assessed using an acceptable goodness-of-fit index.

A number of fit indexes have been recommended by researchers with reasons for such recommendation as seen in Table 5.8. The study will adopt the most suited fit index given the proposed research model.

Table 5.8 Selected fit indices and general rule for acceptable fit

Fit Index	Measure	Description	General rule for acceptable fit
Chi-Square	χ2	Assess overall fit and the discrepancy between the sample and fitted covariance matrices. NB; it is sensitive to sample size	P-values ≥ 0.05 (Parry, 2018) P-values: significant p-value expected (Hair et al., 2010)4* p-values: 0.05 - 1.00 (Good Fit); 0.01 - 0.05 (acceptable fit) (Schermelleh-Engel, Moosbrugger, & Müller, 2003)
Relative Chi-square	χ2 / df	Relative Chi-square is the ratio of chi-square to degree of freedom	χ2/df ≤ 2 or 3 χ2/df 0 – 2 (good fit); 2 – 3 (acceptable fit) (Schermelleh-Engel et al., 2003)
(Adjusted) Goodness of Fit	(A)GFI	GFI is the proportion of variance accounted for by the estimated population covariance. Analogous to R2. AGFI favours parsimony.	GFI ≥ 0.95 (Hoelter, 1983) GFI > 0.90 (good fit) (Crockett, 2012) AGFI > 0.90 (good fit) (Crockett, 2012)
Comparative Fit Index	CFI	Compares the fit of a target model to the fit of an independent, or null model	CFI ≥ 0.90 (Parry, 2018) CFI > 0.92 (Hair et al., 2010)4* CFI 0.97 - 1.00 (Good Fit); 0.95 - 0.97 (Acceptable Fit) (Schermelleh-Engel et al., 2003)
Root Mean Square Error of Approximation	RMSEA	A parsimony-adjusted index. Value closer to 0 represents a good fit	RMSEA< 0.08 with CFI above 0.92 (Hair et al., 2010)* RMSEA 0 - 0.05 (good fit); 0.05 - 0.08 (acceptable fit) (Schermelleh-Engel et al., 2003)
Standardized Root Mean Square Residual	SRMR	The square root of the difference between the residuals of the sample covariance matrix and the hypothesized model.	SRMR < 0.08 with CFI above 0.92 (Hair et al., 2010)4* SRMR 0 - 0.05 (good fit); 0.05 - 0.08 (acceptable fit) (Schermelleh-Engel et al., 2003)
p of Close Fit	PCLOSE	P Close is a p-value for testing the null hypothesis that the population RMSEA is no greater than 0.05	P-close > 0.05 (good fit) (Kenny, 2015)

Adapted from (Hair et al., 2010; Schermelleh-Engel et al., 2003)

5.4.2 Construct Validity and Construct Reliability

Construct validity is the extent to which constructs are accurately represented by the measurement items designed to measure them (Hair et al., 2010), while construct reliability refers to the consistency and stability of the measurement of the construct. The two tests are closely related to each other but

[4] *Hair et al. (2010, p. 672) provided guidelines for using different fit indices to demonstrate goodness-of-fit based on model situations (number of the sample size and number of observed variables). The cited guidelines are based on the study's model situation (Sample size < 250 and observed variable ≥ 30).

play separate roles (Tarhini et al., 2013). Holmes-Smith (2011) emphasised that a factor may be consistent (high reliability) but not accurate (valid), and a factor may be accurate (valid) but not consistent (reliable). In this research, constructs reliability was measured using Cronbach's Alpha with results shown in Table 5.6. Where there are validity issues, Farrell and Rudd (2009) suggest testing for convergent validity and discriminant validity to establish the validity measure. However, Hair et al. (2010, p. 709) revealed that both validity and reliability can be measured using: "Composite Reliability (CR), Average Variance Extracted (AVE) and Maximum Shared Square Variance (MSV)."

5.4.3 Convergent Validity

Convergent validity is "the extent to which measurement items explaining a construct converge or share a high proportion of variance in common" (Hair et al., 2010, p. 689). This can be estimated through factor loadings from CFA or AVE from CFA. A factor with high loadings indicates that the items converged on such factor are explaining the desired construct (Farrell & Rudd, 2009). As a rule of thumb, Hair et al. (2010) suggest that the standardised loading estimates should not be less than 0.5. Preferably, loading estimates of 0.7 or higher are the most appropriate. The AVE is a summary indicator of convergence. Farrell and Rudd (2009, p. 3) defined AVE as "the amount of variance in observed variables that a latent construct is able to explain". According to Fornell and Larcker (1981), AVE is calculated as the mean-variance extracted for the items loading on a construct. It is calculated using standardized loadings with the formula: AVE $= \frac{\sum_{i=1}^{n} Li^2}{n}$

As shown in the formula above, L represents the standardized factor loading and i is the number of items. Similarly to standardised loading estimates, Hair et al. (2010) suggest that an AVE of less than 0.5 indicates that there is more error in the items than explained by the latent factor structure imposed on the measure.

5.4.4 Discriminant Validity

Discriminant validity is a measure of how a construct differs from other constructs within the conceptual framework (Farrell & Rudd, 2009). It is also known as divergent validity. According to Hair et al. (2010), the higher the discriminant validity, the stronger the evidence that a construct is uniquely different from other constructs. To ascertain the level of discriminant validity in this study, the AVE of the construct was compared with the square of the correlation estimate between the constructs (Fornell & Larcker, 1981). Farrell (2010) and Anderson and Gerbing (1988) suggest examining the modification indices and item cross-loadings, using CFA outputs to calculate AVE, and comparing it to shared variance estimates. The AVE is expected to be greater than the squared correlation estimate to support good evidence of discriminant validity (Farrell & Rudd, 2009; Hair et al., 2010).

5.4.5 Model Fit for the Measurement Model

As emphasised earlier by Hair et al. (2010), the model situations (sample size, number of extracted factors and the number of measurement items) of the overall model have an impact in determining the model's fit. The model for this study was made up of a 245 sample size with seven latent factors and 31 measurement items (variables). Based on the listed model characteristics, Hair et al. (2010, p. 672) maintained that χ^2 should give a significant p-value, CFI should be above 0.92, SRMR should be less than 0.90 (with CFI above 0.92) and RMSEA value should be less than 0.08 (with CFI above 0.92). Based on Hair et al. (2010) the result of the CFA model fit as shown in Table 5.9 gave a good model fit. The model fit was within the threshold values recommended by Schermelleh-Engel et al. (2003) and Hair et al. (2010) except for GFI, which was slightly below the commended threshold of 0.90 as against 0.80 shown in Table 5.9.

The result from the measurement statistics as seen in Table 5.10 showed that all variance extracted are above 0.60 where the cut-off value is 0.5. Furthermore, the factor loadings for all composite reliability were all above 0.7, which is a good indication of convergent validity. However, the AVE had two loadings below the recommended 0.5 threshold, which indicates validity concerns (Table 5.11). These two constructs, "Social Influence (SI) and Perceived Cost (PC)" had three measurement items each with their least standardized estimates as 0.55. To resolve the validity concern and improve the model fit, these two measurement items were deleted, and the validity concern issue was resolved by increasing the AVE to above 0.5 as shown in Table 5.12. However, these deleted items did not improve the CFA model fit significantly as shown in table 5.13. Therefore, these two deleted items were re-added back to the CFA model to maintain the minimum of three measurement items for each factor as recommended by Tabachnick and Fidell (2007), since they had an acceptable standardized estimate score above 0.5. Furthermore, Hair et al. (2010) iterated that the threshold rules were only guidelines and advised that more flexibility was acceptable, especially when carrying out an exploratory research. Summarily, Farrell and Rudd (2009) contend that model fit statistics should not be the only bases upon which a CFA will be assessed, rather close attention should be paid to factor loadings, and CFA should not be the only criterion to evaluate convergent and discriminant validity because it is not the most stringent test for discriminant validity. R^2.

Table 5.9 CFA Model fit criteria (before item deletion)

Measure	Measurement Model	Threshold
Chi-square/df (cmin/df)	2.43	< 3 good
CFI	0.92	> 0.95 great; > 0.9 traditional
GFI	0.80	> 0.90 good fit
RMSEA	0.077	< 0.05 good; 0.05 – 0.10 moderate
PLCLOSE	0.99	>0.05 good

Table 5.10 Measurement statistics (before item deletion)

	CR	AVE	SI	AU	PU	IA	ITU	PR	PC
SI	0.73	0.48	0.69						
AU	0.98	0.85	0.32	0.92					
PU	0.92	0.66	0.51	0.56	0.81				
IA	0.92	0.74	0.50	0.60	0.62	0.86			
ITU	0.89	0.62	0.44	0.57	0.84	0.58	0.79		
PR	0.82	0.60	0.23	-0.008	-0.07	-0.13	-0.02	0.77	
PC	0.72	0.48	0.55	0.14	0.12	0.18	0.11	0.42	0.69
*The diagonal entries express the variance extracted. The figures underneath the diagonal are the correlation between constructs									

Table 5.11 Validity concerns in the CFA model

Construct	Validity concerns
Social Influence	Convergent Validity: the AVE for SI is less than 0.50.
Perceived cost	Convergent Validity: the AVE for PC is less than 0.50.

Table 5.12 Measurement statistics (after item deletion)

	CR	AVE	SI	AU	PU	ITU	IA	RA	PC
SI	0.71	0.55	0.74						
AU	0.98	0.85	0.37	0.92					
PU	0.92	0.65	0.52	0.56	0.81				
IA	0.92	0.74	0.53	0.60	0.62	0.86			
ITU	0.89	0.62	0.43	0.57	0.84	0.58	0.79		
PR	0.82	0.60	0.25	-0.01	-0.06	-0.13	-0.02	0.77	
PC	0.71	0.57	0.60	0.12	0.13	0.19	0.11	0.40	0.75

Table 5.13 CFA Model fit criteria (after item deletion)

Measure	**Measurement Model**	**Threshold**
Chi-square/df (cmin/df)	2.46	< 3 good
CFI	0.93	> 0.95 great; > 0.9 traditional
GFI	0.81	> 0.90 good fit
RMSEA	0.077	< 0.05 good; 0.05 – 0.10 moderate
PLCLOSE	0.99	>0.05 good

5.5 Conclusion: Exploratory Factor Analysis and Confirmatory Factor Analysis

The EFA result showed a good indication of uni-dimensionality within the model as the measured items within the constructs proved that they were explaining the underlying construct. The measurement variables were allowed to freely load onto the latent constructs and cross load onto multiple constructs based on how they correlate with each other**.** The EFA revealed that one factor COM has to be deleted from the preliminary measurement model because the items explaining them had low factor scores and they mostly cross-loaded on other latent constructs. The EFA also helped to identify strongly correlated measurement items as witnessed between ITU and PEOU which cross-loaded as one factor, explaining users' attitudes towards mobile phone applications while PU and PE cross-loaded as one factor, explaining users' perceptions towards the usefulness of mobile applications. Lastly, SE cross-loaded with AU as one factor explaining users' experience with mobile phone applications. At the end of EFA, seven factors were extracted, and all the factors had at least three variables explaining them. These extracted factors were tested for convergent and discriminant validity in CFA.

CFA result helped to ascertain both discriminant and convergent validity. The model fit showed an acceptable threshold in the chosen assessment criteria except for GFI which was slightly below the recommended threshold. But based on other measurement criteria such as composite reliability, comparative fit index (CFI), Cronbach's alpha, EFA factor loadings and standardised estimate scores, the model was considered to be acceptable to use in SEM.

5.6 Structural Equation Modelling (SEM)

SEM is the process of representing a theoretical model with a set of structural equations through a visual diagram (Hair et al., 2010). SEM was used to conceptually represent the structural relationship between constructs in the research model. The structural relationships were empirically denoted by structural parameter estimates or path estimate. The SEM analysis was carried out using IBM® AMOS® software version 25. In conducting SEM, seven factors extracted during EFA were used to specify the structural model relationships which replaced the correlational relationships found in the CFA model (Hair et al., 2010). SEM helped to simultaneously examine the direct and indirect relationships between the constructs in the proposed model. It also helped to test the hypotheses formulated after EFA as well as test the model fit between the hypothesized structural model. The structural model, on the other hand, applied the structural theory by specifying which constructs are related to each other and the nature of each relationship (Hair et al., 2010).

Below is the structural model for the adoption of mobile phone applications. The emphasis on the model is on the nature and magnitude of relationships between the constructs.

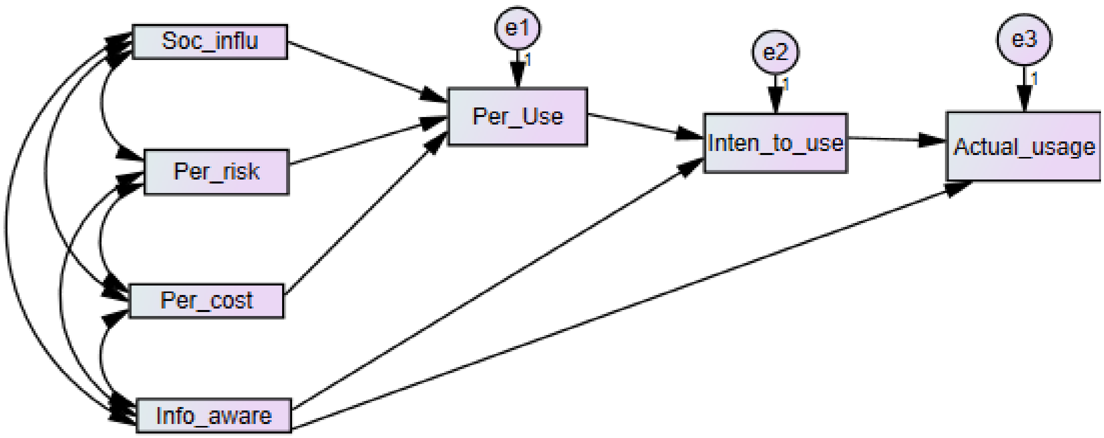

Figure 5.4 Hypothesised structural model for the adoption of mobile phone applications

Following the same measurement criteria used for the measurement model (Figure 5.3), the structural model gave a good model fit as seen in Table 5.14. The model fit was within the threshold values recommended by Schermelleh-Engel et al. (2003) and Hair et al. (2010, p. 55).

Table 5.14 Model fit criteria for the structural model

Measure	Measurement Model	Threshold
Chi-square/df (cmin/df)	1.82	< 3 good
CFI	0.99	> 0.95 great; > 0.9 traditional
GFI	0.98	> 0.90 good fit
AGFI	0.94	> 0.80 good
RMSEA	0.058	< 0.05 good; 0.05 – 0.10 moderate
PLCLOSE	0.34	>0.05 good

Table 5.15 The estimation for regression weights of the hypothesized model regression weights: (Group number 1 – Default model)

			Estimate	S.E.	C.R.	P	Standardised coefficients
PU	<---	SI	1.284	0.1	12.816	***	0.803
PU	<---	PR	-0.175	0.071	-2.46	0.014	-0.137
PU	<---	PC	-0.394	0.09	-4.392	***	-0.304
ITU	<---	IA	0.053	0.029	1.813	0.07	0.069
ITU	<---	PU	0.767	0.035	22.182	***	0.847
AU	<---	IA	0.796	0.117	6.781	***	0.41
AU	<---	ITU	0.861	0.154	5.611	***	0.34

Significance levels: p<0.01 ***

The SEM results from the estimation for regression weights of the hypothesized Model in Table 5.15 showed a significant relationship between the dependent and the independent variables in the research model. Having achieved a good model fit, the hypothesised relationships within the structural model were examined next.

5.6.1 Hypotheses Results Testing

From the final model shown in Figure 5.4, the seven proposed hypotheses in the structural model were supported (Table 5.16). The final model comprised seven variables which are: (Information/Awareness (IA), Perceived Cost (PC), Perceived Risk (PR), Perceived Usefulness (PU), Social Influence (SI), Intension to Use (ITU) and Actual Usage (AU).

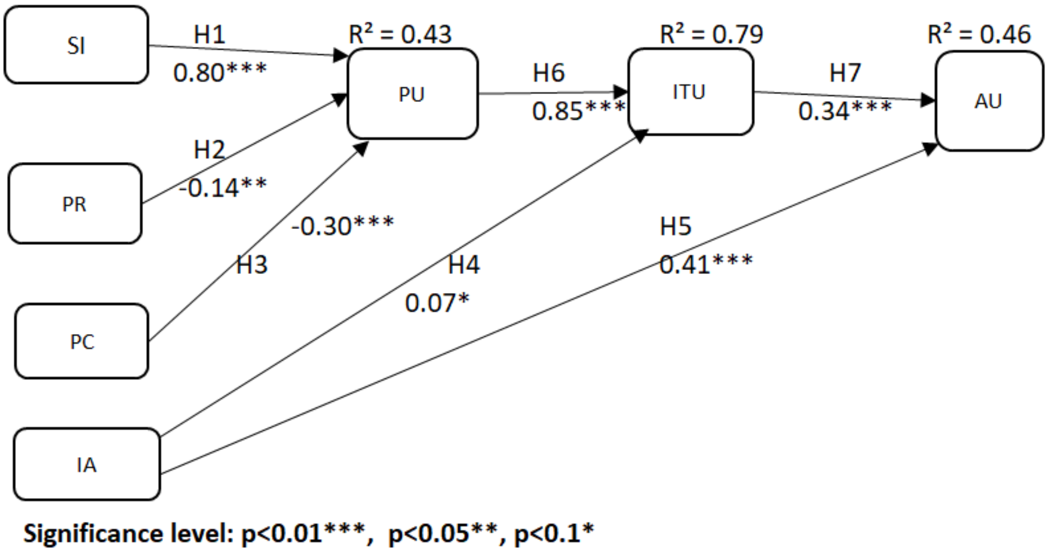

Figure 5.5 Empirical results of the structural model for factors affecting the adoption of mobile applications

The results in Figure 5.5 showed that SI had a significant positive effect on the perceived usefulness (PU) of mobile applications ($\beta = 0.80$, $p < .01$) supporting hypothesis H_1. This indicates that the more people who are important to a farmer use mobile apps or think a farmer should use mobile apps, the more likely it is that he will perceive mobile apps to be useful which can eventually lead to adoption. The SEM result further showed that PR had a significant negative effect on the perceived usefulness (PU) of mobile applications ($\beta = -0.14$, $p < .05$), supporting hypothesis H_2. This implies that risk-averse farmers would not perceive mobile applications to be useful because they consider them to be unsafe. Similarly, PC showed a significant negative effect on the perceived usefulness (PU) of mobile applications ($\beta = -0.30$, $p < .01$), supporting hypothesis H_3. This indicates that farmers who consider the cost of using mobile apps to be high would likely to have a negative perception of their usefulness. The study results also showed that IA has a significant positive effect on farmers' intention to use (ITU) mobile applications ($\beta = 0.07$, $p < .1$) supporting hypothesis H_4. This indicates that the more informed and aware the farmers are about the existence and uses of a mobile app, the higher their intention to use such mobile apps will be. IA also showed a significant positive impact on the actual usage (AU) of mobile applications ($\beta = 0.41$, $p < .01$), supporting hypothesis H_5. This would be an outcome proceeding from a positive impact of IA which would lead to actual usage of mobile applications. The SEM result showed that PU of mobile applications has a significant positive impact on farmers' intention to use

(ITU) mobile applications (β = 0.85, $p < .01$), while ITU had a significant positive impact on the actual usage (AU) of mobile applications (β = 0.34, $p < .01$). This supports hypotheses H_6 and H_7. It goes on to show that farmers who perceive mobile apps to be useful will develop a positive intention towards their usage. This positive intention to use will, in turn, lead to actual usage.

The results of the squared multiple correlations (SMC) from the dataset showed that SI, PR, and PC accounted for 43 percent (R^2 = 0.43) of the variance of PU of mobile application, with SI having the only significant positive effect. On the other hand, PU and IA explained 79 percent (R^2 = 0.79) of the variance of farmers' ITU mobile applications, while ITU and IA explained 46 percent (R^2 = 46) of the variance of AU of mobile applications.

Table 5.16 Standardised regression coefficient

Hypotheses	**Path**	**Support**	**Regression weight**
H_1: SI has a significant and positive impact on the perceived usefulness of mobile applications	SI → PU	Yes	0.80***
H_2: PR has a significant and negative impact on the perceived usefulness of mobile applications.	PR → PU	Yes	-0.14**
H_3: PC has a significant and negative impact on the perceived usefulness of mobile applications.	PC → PU	Yes	-0.30***
H_4: IA has a significant and positive impact on farmers' intention to use mobile applications	IA → ITU	Yes	0.07*
H_5: IA has a significant and positive impact on the actual usage of mobile apps	IA → AU	Yes	0.41***
H_6: PU has a significant and positive impact on a farmers' intention to use mobile applications.	PU → ITU	Yes	0.85***
H_7: ITU has a significant and positive effect on actual usage of mobile apps	ITU → AU	Yes	0.34***

Significance levels: p<0.01 ***, p<0.05 **, p<0.1*

Table 5.16 presents the summary of the hypotheses and the regression weight of all the path coefficients in the structural model. Four exogenous variables (SI, PR, PC and IA) and three endogenous variables (PU, ITU and AU) were tested in the overall model. Four of the exogenous variables were found to be significant determinants of the three endogenous variables. Though the structural model gave a good fit, Hair et al. (2010) warned that good fit alone is insufficient to support a proposed structural theory. He suggests that the individual parameter estimates should be considered to ensure that they are statistically significant in their predicted direction. According to Cohen (1988), standardised regression weights less than 0.1 are considered small, those around 0.3 are considered medium while those greater than or equal to 0.5 are considered large. All seven paths in the structural model were significant and they support the hypothesized theory. Going by Cohen's approval, the regression weights of the significant paths range from small to large (0.1 to 0.8).

5.7 Conclusion: Structural Equation Modelling

The fit indices for the structural model were in the acceptable level and as a result, there was no need for model refinement. Also, the result of the structural model showed that all seven direct hypothesised relationships were supported (Table 5.16). The structural model exhibited a strong explanatory power, which showed the extent to which the model explains variance in the data set. The exogenous variables SI, PR and PC accounted for 43 percent (R^2 = 0.43) of the variance of perceived usefulness (PU) of mobile applications. PU and IA explained 79 percent (R^2 = 0.79) of the variance of intention to use, while ITU and IA explained 46 percent (R^2 = 0.46) of the variance of farmers' actual usage (AU) of mobile applications.

CHAPTER SIX

6.1 Discussion and Conclusions

This study was aimed at providing a critical understanding of the current state of mobile apps use in the Nigerian agricultural sector by examining the types of phones used, the operating systems used, the mobile applications used and the factors that affect the adoption of mobile applications by farmers. To achieve this purpose, descriptive statistics were employed to understand the current state of mobile phone and application usage. Based on the extended Technology Adoption Model (TAM2) Structural Equation Modelling (SEM) was used to understand the factors that influence the adoption of mobile applications. The results from the study helped towards an understanding of the current state of mobile apps use and the factors that affect the adoption of mobile applications by farmers.

Chapter Four presented a detailed analysis of results using descriptive statistics with the help of IBM® SPSS® Statistic 25 and Microsoft Office Excel 2016. The results showed the types of phones and the operating systems on the phones used by farmers, the current applications being used by the farmers, factors that distinguish farmers who use mobile applications from those who do not use mobile apps, and lastly, the level of interest and willingness of farmers to use mobile applications in their daily farming activities.

The need to understand the type of phones used by farmers in this study was very important because it was a major determinant as to the possibility of using mobile applications. The study showed that 69 percent of the farmers used smartphones while 31 percent used low-end mobile phones. This is a strong indication of widespread smartphone usage in Nigeria and other sub-Saharan African countries as found by Rachel (2016), Poushter (2016) and Poushter, Bishop, and Chwe (2018). The study further revealed the operating systems being used by the farmers and the Android operated system appeared to be the most used with 83 percent of the farmers using it. The least used operating systems were Windows and iOS which had a combined seven percent usage. These findings are in line with the findings by Adesina (2014), Costopoulou et al. (2016) and Lim et al. (2014).

Regarding the applications used by the farmers, the study identified 12 different mobile applications (Table 4.8). WhatsApp and mobile banking apps were the most used while Hello Tractor and Instagram were the least used mobile apps by the farmers for farming activities (Figure 4.2).

The demographic variables of the farmers such as gender, age and educational level were assessed in comparison to smartphone ownership and usage for farm activities. Male farmers appeared to own and use mobile apps in their farming activities more than female farmers (Figure 4.4). This result is consistent with prior findings (Evans et al., 2013; Rachel, 2016). The Millennials and Generation X farmers owned most smartphones and used mobile applications for their farming activities. This result is in line with previous findings (Jiang, 2018; Poushter, 2016; Poushter et al., 2018). Farmers who were educated mostly owned smartphones and used mobile apps for their farm activities. This is evidenced in the study findings where over 90 percent of the farmers with either primary education or no formal education had no smartphone. In reverse, over 90 percent of the farmers with tertiary education owned a smartphone, while over 85 percent used mobile apps. This shows the level of impact education has on the use of smartphones and mobile apps. Previous studies support these findings (Aker, 2011; Coyle & Williams, 2016; Poushter, 2016; Rachel, 2016).

The level of interest in and willingness of farmers to use mobile applications were assessed through the responses from some of the survey questions. The responses to these questions showed a high level of interest in mobile applications (Table 4.11).

Chapter Five presented the results of factors that influence the adoption of mobile applications by farmers in Abia state. This was achieved using Structural Equation Modelling (SEM) with the help of IBM® AMOS® software version 25. Seven factors were extracted from Exploratory Factor Analysis (EFA). The extracted seven factors were Social Influence (SI), Perceived Cost (PC), Perceived Risk (PR), Perceived Usefulness (PU), Information/Awareness (SI), Intention to Use (ITU) and Actual Usage (AU). SEM was used to analyse the causal relationships among the seven factors (constructs) in the research model. The structural model provided a good fit. It also showed that seven of the direct hypothesised relationships in the research model were supported (Table 5.16). This shows that the study's proposed model represents the data adequately. The proposed model, extended TAM, showed a high predictive ability in explaining the factors that influence the adoption of mobile applications by farmers.

Going by previous studies on technology adoption (Kim et al., 2007; Malik et al., 2017; Wu & Wang, 2005), this study affirms the suitability of extended TAM in comprehending and explaining the mobile applications adoption behaviours of farmers. The results showed that the exogenous variable social influence (SI) had a significant positive impact on the perceived usefulness (PU) of mobile apps. This result is in line with Hakkak et al. (2013), Kesharwani and Singh (2012) and Lee, Kim, and Choi (2012). SI is the impact of the opinions, views and reviews of other people who are important to a user and which influence their decision regarding the adoption of mobile applications (Eckhardt, Laumer, & Weitzel, 2009; Malik et al., 2017). This result showed that farmers perceive mobile apps to be useful because people who are important to them are using them. These important people could be fellow farmers or an extension officer. The indirect effect of this positive relationship between SI and PU will result in a positive intention to use (ITU) mobile apps which can eventually lead to actual use or adoption of mobile apps. In contrast, some studies found that SI did not have a significant effect on the perceived usefulness of some ICT (Arenas Gaitán, Peral Peral, & Ramón Jerónimo, 2015; Venkatesh et al., 2003). These researchers argued that SI is only crucial in a compulsory situation and especially in the early stages of the experience when the opinions of the potential user are relatively unreliable. However, their study focus was not on farmers and farming mobile applications where such relationships have not been considerably examined.

The study results further showed that perceived risk (PR) had a significant negative effect on farmers' perceived usefulness (IU) of mobile applications. This result is consistent with Kesharwani and Singh (2012) and Wu and Wang (2005). PR in the study context referred to farmers' attitude towards risk, which had been found to influence their perceptions of the usefulness of ICT, as they perceive it to expose their privacy which can lead to losses. The negatively perceived usefulness had an indirect negative impact on farmers' intention to use mobile applications. This was because farmers who thought mobile apps were risky to use would consider them not to be useful, and therefore would have a negative intention towards their usage.

The study revealed that perceived cost (PC) had a significant negative impact on the perceived usefulness (PU) of mobile applications. PC in the study context referred to the cost a farmer paid to either get access to an application or subscribe to the services offered through an application. Similar studies on ICT adoption found PC to negatively affect intention to use (ITU) (Kim et al., 2007; Wu & Wang, 2005). Brown et al. (2013) reported that most smallholders are price sensitive, and they tend to react to small changes in service fees. In the case of mobile applications used by farmers in this study, most of them were free to download and do not require subscription fees to enjoy the services, but farmers had to pay for internet subscriptions before they could use the applications. The response from the farmers indicated that internet subscription cost was quite significant. A similar study on the adoption of mobile internet by Kim et al. (2007) revealed that perceived fees/cost have a significant negative effect on the adoption intention of users because having to pay a price at all prevents new customers from trying services they are not sure about. This further justifies the significant negative effect of PC on mobile apps adoption because most of the applications cannot work without the internet. And internet access requires a cost.

The study results also showed that information/awareness (IA) had a significant positive impact on farmers' intention to use (ITU) mobile apps and the actual usage (AU) of mobile apps. This result is in line with Aker (2011), Klotz, Saha, and Butler (1995) and Hakkak et al. (2013). IA in the study context referred to the knowledge a person had about the existence and uses of a mobile application, which led to the decision to use such application (Chan et al., 2011). Stiglitz (2000) reported that we live in a world of imperfect information. According to Aker (2011, p. 6), "information asymmetries are often an important constraint to technology adoption in developing countries." This study found that most farmers were disadvantaged on the benefits of mobile applications because they had no prior knowledge of the existence of some the available agricultural mobile applications. This affected their behavioural intention to use mobile apps, which would ultimately lead to actual usage of mobile applications. If a farmer was informed about the existence of an app, chances were that the farmers might use such an application. The implication is that the higher the awareness of the existence and usefulness of a mobile application, the higher the likelihood of a farmer installing and using such an application.

The results also showed that perceived usefulness (PU) had a significant positive impact on farmers' intention to use (ITU) mobile applications. PU in the study context referred to the degree to which a farmer believed that using a mobile app would enhance his/her farming activities. If a farmer found a mobile app to be useful in his/her farming business, then he/she was more likely to use it. This result is in accordance with previous studies e.g. (Hakkak et al., 2013; Kesharwani & Singh, 2012; Wu & Wang, 2005) which all found PU to have a significant positive impact on ITU ICT. The highly significant level of this result suggests that farmers were more motivated to use mobile apps because of their usefulness.

Finally, the last hypothesised relationship in the proposed model between farmers' intention to use (ITU) and actual usage (AU) of mobile apps showed that ITU had a directly significant positive effect on actual usage of mobile applications. This result is consistent with Abdekhoda et al. (2016), Arenas Gaitán et al. (2015), Wu and Wang (2005) and Venkatesh et al. (2003), who all found a significant positive effect between behavioural intention to use and the actual usage/adoption of information communication technologies. The results indicate that if farmers have a strong intention to use mobile applications in their farming activities, then they are most likely to use them.

The study, in general, explained the fundamental relationships between the proposed external variables and the original TAM variables. The results are in line with previous studies, and show that SI, PR, PC, IA, PU and ITU are all crucially significant variables in deciding the factors that affect the adoption of mobile applications by farmers in Abia State. The study demonstrates that extended TAM is a suitable model to explain the factors that influence mobile apps adoption.

6.2 Theoretical Implications

The main aim of this study was to provide a critical understanding of the current state of mobile apps use in the Abia State agricultural sector and the factors that affect the adoption of mobile applications by farmers. The study adopted an extended TAM framework in explaining the factors that influence the adoption behaviours of farmers towards mobile apps. The study contributes to mobile applications and ICT adoption literature in the following ways:

The literature review showed that limited research had been carried out on the adoption of mobile applications by farmers for agricultural purposes. This study provides an understanding of mobile apps adoption behaviour in agricultural settings. The extended TAM framework adopted for the study was modified by three external variables: Perceived Risk (PR), Perceived Cost (PC) and Information/Awareness (IA), with their effects examined on the original TAM variables: Perceived Usefulness (PU), Intention to Use (ITU) and Actual Usage (AU). These three external variables were found to be important predictors of the original TAM constructs in determining the factors that influence the adoption of mobile applications by farmers. Based on the study results, SI, PC, PU and IA had the most significant effect on farmers' intentions to use mobile apps and the actual usage of mobile apps. SI had a positive direct effect on PU and a positive indirect effect on ITU and AU through PU. PR and PC had a negative direct effect on PU and a negative indirect effect on ITU and AU. IA had a weak direct effect on ITU and a very strong direct effect on actual usage. From the study results, SI, PC and IA play the most important direct role on PU and AU, while PU and ITU play the most important indirect role for SI, PR and PC in the extended TAM research model for the adoption of mobile applications by farmers.

The study showed the level of importance of IA as a predictor of behavioural intention and actual usage in the context of mobile apps adoption. Most empirical studies on technology adoption using TAM have ignored this important variable, especially in an agricultural setting. This study, therefore, lays a good theoretical foundation for other research using extended TAM to examine the impact of IA on the adoption of the ICT being studied.

This research also demonstrated the empirical applicability of extended TAM in studying technology acceptance in a developing country context such as Nigeria. As Tarhini et al. (2013) noted, TAM has not been widely applied in studying technology adoption in developing countries. Most TAM studies focus on developed countries e.g. (Davis, 1989; Kim et al., 2007). As a result, Teo, Luan, and Sing (2008) highlighted the importance of applying TAM in different cultural settings to eliminate the argument that Davis (1989) did not consider cultural differences when he developed TAM. This study, therefore, shows evidence that TAM can be extended and applied in a cross-cultural context of developed and developing countries.

Finally, the study results validated the explanatory power of extended TAM in analysing farmers' mobile apps adoption behaviours for various mobile applications.

6.3 Practical Implications

This study examined the type of phones used by farmers, the operating system on the phones, the mobile applications being used by the farmers and the factors that influenced the adoption of mobile applications. The overall aim was to understand how best to support and encourage farmers to use mobile apps in their farming activities. The findings from the study revealed some crucial insights to be considered by app developers, policymakers, extension personnel and farmers alike for an effective use of mobile apps in improving farmers' productivity.

The study revealed that over 69 percent of the farmers use smartphones, which was a positive indication that the majority of the farmers stood a chance of benefiting from the services rendered through mobile applications. Out of this 69 percent that uses smartphones, 84 percent of them used the Android operating system. This shows that app developers should focus more on building apps that are compatible with the Android operating system, as they stand a higher chance of reaching most of the farming population.

The empirical result showed that SI, PU and IA had a positive influence on farmers' intention to use mobile apps and the actual usage of mobile applications, while PR and PC had a negative direct impact on the perceived usefulness of mobile apps. This negative direct impact of PR and PC results in a negative indirect effect on farmers' intention to use mobile apps and the actual usage of mobile apps. PU contributed the most to ITU compared to IA. This shows that farmers who find mobile apps to be useful are more likely to adopt them in their farming activities. This result suggests that more effort should be put into educating the farmers on the usefulness of mobile apps. This can be done by the extension officers, and by so doing, farmers will develop more positive intentions to use mobile apps, which will lead to actual adoption. For the app developers, they should put more effort in putting quality and useful contents in the apps that they develop for farmers. By doing so, more farmers will adopt such apps.

Information awareness (IA) was one of the most important variables included in the research model. The empirical result showed that it had a positive impact on both ITU and AU, but a stronger impact on AU. The result suggests that lack of awareness of the availability of mobile apps and their uses is the reason most farmers are not using mobile apps. More awareness needs to be created, especially when a new mobile app has been developed. This can be done through various mass media and social media outlets and also through various centres where farmers have their extension meetings. This would help to increase the use of agricultural mobile apps by farmers.

Perceived risk (PR) was one of the external variables that had a negative impact on the perceived usefulness (PU) of mobile applications. The study showed that farmers who were risk-averse towards ICT perceived mobile apps not to be useful and therefore had a negative intention to use mobile apps. Farmers in general need to be reassured of their safety when dealing with internet applications that involve exchanging of information (sometimes personal information). App developers and other stakeholders such as financial institutions, government agencies and extension officers need to incorporate significant actions to increase trust amongst the farmers. This would help reduce perceived risk as well as increase farmers perceived usefulness of mobile apps and their intention to use mobile apps.

Perceived cost (PC) was the second external variable that had a negative impact on the perceived usefulness (PU) of mobile applications. With regard to agricultural mobile apps, most of them are free of charge to download and use. But the farmers noted that the cost of internet subscriptions (an enabling factor to use mobile apps) was high. Consequently, this had a negative effect on the perceived usefulness of mobile apps. Policy makers should work on reducing the high cost of internet subscriptions, or at the very least, subsidise the cost for farmers. This would encourage them to develop a positive intention towards the use of mobile apps.

The study highlighted the importance of education among the farming population in the use of smartphones and mobile apps. The study showed that the majority of the farmers that used mobile apps were the educated farmers (See Figure 4.6). This shows that training and educating farmers will have a more positive impact on the adoption of mobile apps. This would also have a positive impact on social influence because the greater the number of farmers using mobile apps, the higher the chances that other non-apps users who are close them will start using mobile apps. SI positively affects PU, which leads to a positive ITU.

In conclusion, this study provides the views and opinions of farmers on the essential factors that affect their intention to use and actual usage of mobile apps to app developers. From the study, farmers can also know the factors that lead them to accept mobile applications. Finally, the study provided a model that enabled farmers, app developers, policy makers and extension officers to understand the factors influencing farmers' intention to adopt and use mobile apps in their farming activities.

6.4 Conclusion

This research examined the current level of mobile apps use for agriculture in Abia State and the factors that affect the uptake of this technology. It uncovered the types of phones and the operating systems on the phones used by farmers and the current mobile applications being used by farmers. The study also revealed farmers' level of interest and willingness to use mobile apps in their daily farming activities.

Descriptive statistics were used to summarize the demographic information of the farmers in the study area using tables, figures, charts and graphs. This helped to achieve the first three objectives of this study, while SEM was used to analyse and present the causal relationships among the constructs in the proposed research model. An extended TAM framework was estimated to identify the factors that affected the adoption of mobile apps. The results prove that extended TAM is a good predictor of farmers' adoption behaviour towards mobile applications.

This study contributed extensively to farmers' technology usage literature through its findings. It helped to bridge the information gap between agricultural app developers and farmers by revealing some important demographic information of farmers such as their age, gender, educational level, the type of farming carried out and most importantly, the factors that affected the adoption and continuing use of mobile apps.

6.5 Limitations of the Study

This thesis encountered some limitations during the study process which impacted the overall outcome of the study. With regard to data collection, a convenience sampling technique was employed as it was very difficult to track down the farmers individually in their farms. As a result, they were collectively surveyed during their extension meetings in three different agricultural zones in the study location (Abia State). This meant that farmers who were not part of the group were likely to have been omitted from the survey. Although the 245 valid samples from the three zones were believed to be a good representation of the sampling population in the study area, the fact the study was conducted in one state in Nigeria limits the generalisability of the findings to the entire Nigerian farming population.

Caution should also be applied when generalizing the result to other developing countries apart from Nigeria. Even though extended TAM suited the study data well, cultural country differences might affect the suitability of TAM for similar studies in other developing countries.

Another limitation is that the study looked at the use of mobile apps from a generalised view without focusing on any agricultural mobile app in particular. A farmer's perception of one mobile app might be different from another app. The study did not take into account the different perceptions of the various mobile apps available.

The study employed a quantitative approach in data collection and its analysis. This was due to time and resources constraints. Although the questionnaires were designed based on theoretical grounds and reviewed technology adoption literature, the inclusion of a qualitative approach to the study would have given a more in-depth understanding of the factors the influenced the adoption of mobile apps by farmers in the study area.

Finally, the study analysis revealed that some of the questions were interpreted differently by the farmers from their intended meaning. This was evidenced in the outcome of EFA where some measurement items cross-loaded on each other as one construct. However, EFA and CFA analysis helped to identify common themes and patterns in the measurement items (survey questions). This helped to reduce items to latent factors based on the underlying structure of the data.

6.6 Future Study Directions

This thesis suggests some important future study directions as follows:

The present study focused on a state in one region of Nigeria. A similar study can be replicated in another state or region to ascertain if a similar result will be obtained. This would further help to validate the study result on factors that influence the use of mobile apps by farmers across Nigeria.

This study looked at mobile apps in general without focusing on any app in particular. However, the reason for adopting one app may be different from the reason for adopting another app. Therefore, it will be worthwhile to treat the applications individually to see what affects the adoption of each.

Future studies can also look at the impact of the identified mobile apps used by farmers in this study. For instance, this study identified WhatsApp and Mobile Banking Apps as the most used mobile apps by the farmers but failed to look at the impact of using these apps in the farmers' productivity. Future studies should look at the individual impact of these mobile apps in improving farmers' productivity.

Given the quantitative approach employed in this study for both data collection and analysis, future studies can explore a qualitative approach or both, to get a more in-depth knowledge of the factors that influence the adoption and continued use of mobile apps by farmers.

The inclusion of information/awareness (IA) in the study's extended TAM showed that IA is an important determinant in the adoption of mobile applications by farmers. This variable (IA) can be applied to other technology adoption studies than those of mobile applications for agriculture, such as different technologies in diverse fields.

Finally, the study did not examine the statistical impact of demographic variables in the adoption of mobile applications. Therefore, future studies could investigate the impact of demographic variables on mobile apps adoption behaviour.

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Appendices

Appendix A: Mobile Application Descriptions

Mobile Application	Country	Category	Description
ProbityFarms	Nigeria	Productivity agricultural mobile apps	Provides farmers with a farm management and accounting platform.
Compare-the-market	Nigeria	News/information agricultural mobile apps	Helps farmers and their customers to compare the daily market prices of agricultural produce
FarmCrowdy	Nigeria	News/information agricultural mobile apps	Designed to connect investors who are interested in investing in any farming initiative of their choice by sponsoring farmers
Hello Tractor	Nigeria	News/information agricultural mobile apps	Connects farmers who are interested in hiring tractors or other modern farming equipment from potential owners
AgroData	Nigeria	News/information agricultural mobile apps	Designed to fill this gap by linking the farmers to agricultural research institutes where they can now easily get new knowledge that will improve their farming productivity.
WhatsApp and Telegram	Various countries	Social media mobile apps	Used for socialising, sharing ideas and receiving desired information from fellow farmers in the group. They are also used for extension services
Cellulant	Nigeria	News/information agricultural mobile apps	Designed as an e-wallet to help farmers redeem government subsidies on fertilisers and seeds.
GES E-wallet	Nigeria	News/information agricultural mobile apps	Provides soft loans to farmers, tracks seed and fertiliser disbursement and educates farmers on farming methods that will improve their output
Mobile banking app	Various Countries	Productivity agricultural mobile apps	Used for making payments. Saves time and reduces transaction cost
MKisan	India	News/information agricultural mobile apps	A government portal designed to provide farmers and other stakeholders with expert advice and information.
Krishiville	India	News/information agricultural mobile apps	Provides information on weather, commodity prices and agricultural news.
F-tack Live	Australia	Productivity agricultural mobile apps	Farm management app that allows the user to record and access information in real time
Modisar app	Botswana	Productivity agricultural mobile apps	Designed to help farmers manage their livestock by recording their stock, income and expenses
Virtual City AgriManager	Kenya	Productivity agricultural mobile apps	Designed to automate input purchasing transactions at a reduced cost and time
KilimoSalama	Kenya	Productivity agricultural mobile apps	Provides insurance services to farmers from losses caused by weather vagaries or natural disasters.

M-Pesa	Kenya	Productivity agricultural mobile apps	Used for making payments, receiving payments and storing money easily.
KACE (Kenyan Agricultural Commodity Exchange)	Kenya	News/information agricultural mobile apps	Provides daily price information on farm output and also facilitates contract negotiation and produce transport
DrumNet	Kenya	News/information agricultural mobile apps	Provides farmers with information on price, market, weather. Also links producers, processing firms, input retailers and transport providers.
Grameen (weather application)	Uganda	News/information agricultural mobile apps	Provides information on weather forecasts
Google Trader	Uganda	News/information agricultural mobile apps	Links buyers and sellers as well as enabling them to display their goods
WeFarm	Uganda, Kenya, Tanzania	Social media mobile apps	Enables registered farmers to ask questions and receive answers to their questions
Infotrade	Uganda	News/information agricultural mobile apps	Collects market data on 46 commodities from 20 districts, analyses the data and provides useful information to the farmers
Foodnet and Farmgain	Uganda	News/information agricultural mobile apps	Provides market information on prices and trade volumes
Esoko	Uganda, Ghana, Kenya Nigeria, Tanzania, Zambia, and Cote d' Ivoire	News/information agricultural mobile apps	Provides updated price information to farmers on English and local dialects.
Cocoa Link	Ghana	News/information agricultural mobile apps	Provides farmers with information relating to weather, pests and diseases, farming practices and answers to questions in real-time
M-kilimo	Tanzania	News/information agricultural mobile apps	Provides farmers with extension and market information services relating to new seeds or technology, pest and disease outbreaks, planting seasons and commodity prices

Appendix B: QUESTIONNAIRE

My name is Victor Okoroji, and I am a student at Lincoln University, New Zealand.

This questionnaire is being administered to obtain some information for research on the topic, "Farmers' use of mobile phone applications in Abia State, Nigeria". Taking your time to complete this questionnaire would be highly appreciated. The questionnaire will take less than 30 minutes to complete. Your information will be kept confidential, and your anonymity is guaranteed. Information obtained will be compiled and analysed at Lincoln University. This research is voluntary, and you can withdraw anytime.

Please, if you have any questions, you can contact me on this number 08067686614 or email; victor.okoroji@lincolnuni.ac.nz

Thank you,

Victor Okoroji

N.B. The term "**Agricultural Mobile Application**", refers to any mobile application that you use for your farming activities, e.g. to receive information (price, weather or market updates), record your farm operations or make and receive payments for your farm inputs and outputs.

Part 1. Demographic characteristics of the respondent

1. Gender: ◯ Male ◯ Female
2. Age Group: ◯ 18-25 ◯ 26-40 ◯ 41-60 ◯ over 61
3. Marital Status: ◯ Single ◯ Married ◯ Widowed ◯ Divorced
4. Educational Level:No Formal Education ◯ Primary ◯ Secondary ◯ Tertiary
5. Family Size: …………………………………………..
6. Farm Size (In hectare, acre or plot):…………………………………………..
7. Years of Experience: …………………………………………..
8. Type of Farming: ◯ Crop farming ◯ Livestock ◯ Poultry ◯ Fishery

   Other, Please Specify …………………….

   If more than one farming type, which is the main one? …………………………………………………….
9. What percentage (%) of your produce do you consume:◯less than 10% ◯11-25%

   ◯ 26-50% ◯ 51-80% ◯ 80-100%

10. How often do you attend extension meetings:

Always	Most of the times	sometimes	Rarely	Never

Part 2.

11. I have a smartphone? ◯ Yes ◯ No

12. Smartphone Operating System: ◯ Android ◯ IOS ◯ Windows ◯ Blackberry

13. I use mobile applications for my farming activities? ◯Yes ◯No

Mobile applications that I use (Please tick all that applies):

Tick (√)	Mobile App	Level of Use				
		Always 1	Most of the time 2	Sometimes 3	Rarely 4	Never 5
	ProbityFarms					
	Compare-the-market					
	FarmCrowdy					
	Hello Tractor					
	AgroData					
	WhatsApp					
	Telegram					
	Cellulant					
	GES E-wallet					
	Mobile banking App					
Other, please specify						

Part 3A. Please tick one box for each question

Construct	**Strongly agree**	**Agree**	**Neither agree nor disagree**	**Disagree**	**Strongly disagree**	**Don't know**
Information/Awareness (IA) (Chan et al., 2011)						
I know of many mobile applications that could be used for agriculture						
I know farmers are receiving useful information through mobile applications						
I know many farmers are actively using mobile apps to help them improve their farming business						
I know that mobile applications could be used for agricultural						

purposes						
Compatibility (COM) (Chan et al., 2011)	**Strongly agree**	**Agree**	**Neither agree nor disagree**	**Disagree**	**Strongly disagree**	**Don't know**
Agricultural mobile apps are compatible with my smartphone						
Using agricultural mobile apps fit the way I like to manage my farm						
Mobile apps are suitable for the type of farming I do.						
Price/cost (PC) (Wu & Wang, 2005)	**Strongly agree**	**Agree**	**Neither agree nor disagree**	**Disagree**	**Strongly disagree**	**Don't know**
I think the cost of using mobile apps is too high						
I think the mobile apps registration fees are too high for me						
There are not enough benefits from using mobile apps to justify the cost						
Mobile apps require a lot of money for data subscription						
Social Influence (SI) (Abdekhoda et al., 2016)	**Strongly agree**	**Agree**	**Neither agree nor disagree**	**Disagree**	**Strongly disagree**	**Don't know**
I am more likely to use agricultural mobile apps because other farmers are using them						
I am more likely to use mobile apps because people who are important to me think I should use them						
I am more likely to use mobile apps because the extension officer recommended mobile apps to all farmers						
Risk aversion (RA) (Wu & Wang, 2005)	**Strongly agree**	**Agree**	**Neither agree nor disagree**	**Disagree**	**Strongly disagree**	**Don't know**
I think mobile apps expose my confidential information						
I think mobile apps can give false information that can lead to loss of income						
I think mobile apps can give false information that can lead to loss of output						
Relying on information from mobile apps is risky						

Performance expectancy (PE) (Chan et al., 2011)	**Strongly agree**	**Agree**	**Neither agree nor disagree**	**Disagree**	**Strongly disagree**	**Don't know**
Using mobile apps makes farming activities easier						
Using mobile apps make it easier to access information						
Using mobile apps help to save time						
Using mobile apps help to make good decisions						
Perceived ease of use (PEOU) (Tarhini et al., 2013; Wu & Wang, 2005)	**Strongly agree**	**Agree**	**Neither agree nor disagree**	**Disagree**	**Strongly disagree**	**Don't know**
Learning to use mobile applications is easy for me						
Mobile apps are clear and easy to understand						
Mobile apps are simple and easy to interact with						
It is easy to get mobile apps to do what I want them to do						
Perceived Usefulness (PU) (Yahyapour, 2008)	**Strongly agree**	**Agree**	**Neither agree nor disagree**	**Disagree**	**Strongly disagree**	**Don't know**
Using mobile applications can improve my productivity						
Using mobile applications can improve my income						
Using mobile applications can help me make and receive payments faster (farm business)						
Using mobile applications will help locate markets and sell my produce						
Intention to use (IU) (Wu & Wang, 2005)	**Strongly agree**	**Agree**	**Neither agree nor disagree**	**Disagree**	**Strongly disagree**	**Don't know**
Given that I have access to mobile apps, I predict that I will use agricultural mobile apps						
I am very enthusiastic about agricultural mobile applications						
I encourage other farmers to use mobile applications						

If you answered NO (do not use mobile apps) to Question 13 above, please stop here. Thank You

Satisfaction/Experience (SE) (Al-Gahtani, 2016)	**Strongly agree**	**Agree**	**Neither agree**	**Disagree**	**Strongly disagree**	**Don't know**

			nor disagree			
I have used mobile apps before and didn’t find them useful						
Mobile apps don’t offer all they promise						
My experience with mobile apps has been very positive						
Actual Usage (AU) (Abdekhoda et al., 2016)	**Strongly agree**	**Agree**	**Neither agree nor disagree**	**Disagree**	**Strongly disagree**	**Don’t know**
I use mobile applications for my farming business very often						
Mobile apps have saved me time and cost						
Mobile apps give me market and price information						
Using mobile apps has helped me in making good farming decisions in the past						