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Full Length Research Paper

Factors affecting the adoption of mobile applications by farmers: An empirical investigation

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In developing countries such as Nigeria, agriculture is the main source of livelihood with over 70% of the population engaged in farming. They are mostly smallholders and subsistence farmers with minimal use of technology and low productivity. The use of mobile applications in agriculture can potentially help smallholders access agricultural information and financial services, improve access to markets and enhance visibility for supply chain efficiency. Unfortunately, due to a lack of uptake of these applications many farmers have not realized the benefits of this technology. This study seeks to explore and examine 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 261 farmers. Data were analyzed using SEM with the help of IBM SPSS and IBM AMOS software. The structural model showed that seven of the hypothesized relationships in the research model were supported. Social influence (SI), Perceived usefulness (PU), Information/awareness (IA) and Intention to use (ITU) affected the Actual Use (AU) of mobile applications positively, while Perceived risk (PR) and Perceived cost had a negative impact on their adoption. This study contributes to the literature on farmers' technology adoption. It provides evidence that the extended TAM is a suitable model to explain the factors that influence mobile application adoption behavior.

Key words: Mobile applications, smartphone, Information Communication Technologies (ICT) adoption, structural equation modelling, extended technology adoption model.

INTRODUCTION

In developing countries such as Nigeria, over 70% of the population engages in agriculture and they are made up of smallholders who cultivate or own farmland less than five hectares (Ofana et al., 2016). These smallholders are often subsistence farmers with out-dated technology and low productivity (Baumüller, 2015). Despite this they produce over 80% of all agricultural output in Nigeria. This level of production is insufficient to feed the growing population of Nigeria, leading to over-dependence on imported food (Nwajiuba, 2012). Nigeria has a population of 196 million with an annual growth rate of 2.63% World Population Review, 2018), which intensifies the

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need to increase food productivity.

The main challenges faced by these smallholders are access to agricultural information on the use of modern technology and practices, access to market, access to financial services and poor extension service delivery (Baumüller, 2012; IFPRI, 2009; Nwajiuba, 2012). International Food Research Institute IFPRI (2009) revealed that these challenges were more pronounced because these smallholders could not afford the cost of using modern technologies and farm practices. However, studies have proven that the use of mobile application in agriculture can help smallholders get access to agricultural information, access financial services, improve access to markets and enhance visibility for supply chain efficiency (Aker and Mbiti, 2010; Baumüller, 2015; Qiang et al., 2012; Vodafone Group and Accenture, 2011).

Mobile applications (mobile apps) are software programmes designed to run on a mobile device such as 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 use of mobile phone applications has helped developing countries like India, Kenya, Uganda, South Africa and Tanzania improve their agricultural productivity (Qiang et al., 2012). Baumüller (2015) asserted that the use of mobile applications for agriculture has the potential to effectively reach and assist rural smallholders. 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; Qiang et al., 2012; World Bank, 2017). Qiang et al. (2012), in their study, found that the use of mobile applications helps smallholders increase income, with lower transaction and distribution costs on output sales and input supplies. Studies have shown Kenyan farmers increased their farm productivity and income by using mobile apps like Virtual City AgriManager, M-Pesa, KACE (Kenyan Agricultural Commodity Exchange), DrumNet and Kilimo Salama (Baumüller, 2013; Kirui et al., 2013). Esoko mobile app and Cocoa Link reduced the asymmetric information faced by Ghanaian farmers (Aker et al., 2016). Modisar mobile app improved livestock production in Botswana (Chukwunonso and Tukur, 2012). M-Kilimo helped Tanzanian farmers receive extension services and market information that ultimately increased their productivity and income (Temu et al., 2016).

Research problem

In Nigeria, the number of mobile apps that could potentially aid agricultural productivity is increasing. Some applications are still at their development stage with a web version already in existence and running. So far, there has been very limited study on mobile application usage by farmers. Most studies focus on mobile phone usage (Asa and Uwem, 2017; Jaji et al., 2017) and not mobile applications usage. These studies do not differentiate between using a mobile phone and the use of mobile phone applications. Lim et al. (2014) reported that most mobile applications fail because it is difficult to understand the needs of users of these apps. This study aims to bridge this gap by analyzing the factors that affect the usage of agricultural mobile applications. The specific objective of the study is to determine the factors that influence the adoption of mobile applications. The study results helped developers and other stakeholders to understand the challenges faced by farmers and the necessary improvements that will enhance the use of mobile applications by farmers.

Technology adoption model

The Technology Adoption Model (TAM) is a theoretical model that attempts to explain the adoption of various Information Communication Technologies (ICT). Before the introduction of TAM, some theories attempted to explain user adoption of technology. Theory of Reasoned Action (TRA) which was developed by Fishbein and Ajzen (1975) was the first that attempted to describe user adoption of technology. TRA explains user behavior from a social psychology point of view. By 1991, Ajzen developed the Theory of Planned Behavior (TPB) as an extension of TRA to address the limitations of TRA. Ajzen (1991) proposes perceived behavioral control in addition to TRA's attitude and social pressure as a factor that influences intentions and actual behavior. TPB tries to address situations in which individuals have no control over. TAM, which was introduced by Davis (1986), was the first to successfully analyze 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.

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 et al., 2017), consumer services such as mobile commerce (Wu and Wang, 2005) and mobile internet (Kim et al., 2007). The first major extension was carried out by Venkatesh and Davis (2000) who tested four different systems in four organizations. 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

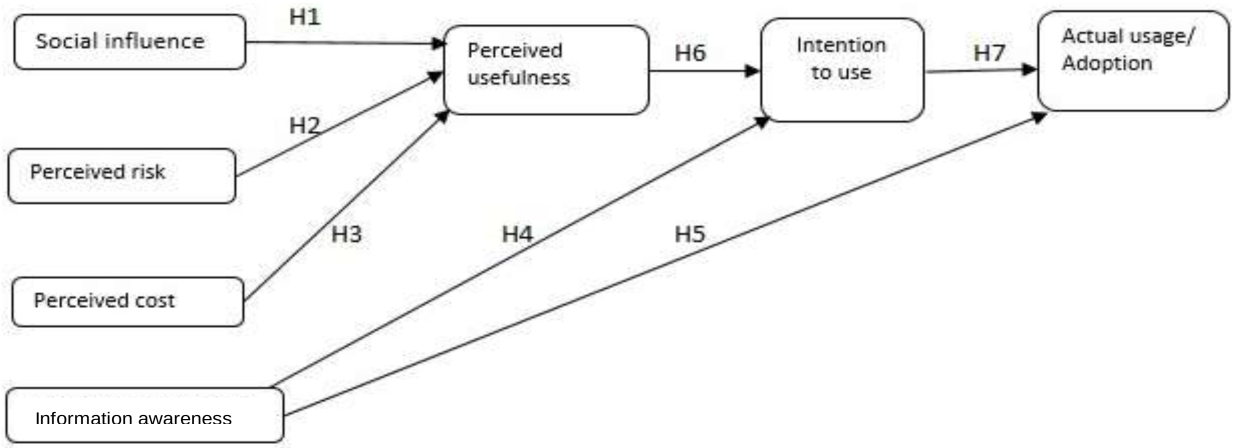

Figure 1. Research model: Adapted from the Extended TAM Model.
Source: Venkatesh and Davis (2000).

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 emphasized the need to add more variables to TAM for the purpose of establishing a stronger model (Legris et al., 2003; Wu and Wang, 2005). As a result of this argument, many studies have come up with various extended versions of TAM to suit the nature of the technology being studied (Chen et al., 2017; Hakkak et al., 2013; Park and Kim, 2014; Venkatesh and Davis, 2000; Wentzel et al., 2013). 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 (Figure 1).

Model development

The workplace environment in an agricultural setting is quite different from the organizational setting in which TAM and its extended version were first applied by Davis (1989) and Venkatesh and Davis (2000). In particular, smallholder farmers' decision making is affected by their socioeconomic characteristics, their biophysical environment and the nature of their farming operations. The importance of these three factors was identified by Baumüller (2012) in his study on the facilitation of agricultural technology adoption among poor farmers.

The extended TAM has been adopted for this study because of its ability to successfully explain and predict the adoption of information technologies. It also provides the flexibility to adapt to different organizational settings. Hence, 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. Although TAM has been modified to suit the study setting, the modification is based on the original extended TAM and utilizes the three factors identified by Baumüller (2012).

Four main original extended TAM constructs were retained in the study proposed model (Perceived Usefulness, Intention to Use, Actual Usage and Social Influence), while three additional constructs were added to modify the original extended TAM to suit the study setting. The three added constructs were Perceived Risk, Perceived Cost and Information Awareness. These constructs were carefully selected from reviewed literature on mobile applications and farmer technology adoption studies.

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 behavioral intention to use ICT or a system (Kesharwani and Singh, 2012; Park and Kim, 2014; Wentzel et al., 2013).

Intention to Use (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) theorized in the original TAM that ITU is a major determining factor in whether or not a potential user will adopt a particular technology. The theory also has it that a person's behavioral intention to use behavioral ITU a given technology is influenced by two beliefs: PU and Perceived Ease of Use (PEOU). In the study context, a farmer's behavioral ITU mobile apps would be a major determinant of whether he eventually uses them.

Social Influence (SI) is a widely recognized factor that influences a person's technology acceptance behavior. 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 behavior 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 and Todd, 1995) have used Subjective Norm and SI 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 and especially in developing countries, extensive social interactions exist between farmers and it 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 favorable or unfavorable.

Perceived Risk (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 and Cox, 1967). They defined PR with regard to the insecurity and unfavorable outcomes associated with consumers' expectations. Internet applications are associated with diverse kinds of risk and as a result, consumers are careful when adopting such technology. PR has been mostly used in internet and mobile banking transaction adoption study because of the security concerns associated with such transactions (Al-Jabri and Sohail, 2012; Kesharwani and Singh, 2012; Wentzel et al., 2013). Most of these studies found PR to negatively influence users' behavioral 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 variable is also important because subsistence farmers rely on their farming output to provide a significant proportion of their food supply. Therefore, the implications of negative outcomes from technology adoption can potentially impact their food security.

Perceived Cost (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, as a result, 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 and Wang, 2005).

Information Awareness (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 (Al-Somali et al., 2009; 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% of Greek farmers did not use mobile agricultural apps because they were not aware of their availability.

Research hypotheses

(i) PU has a direct positive impact on a farmer's intention to use mobile applications.
(ii) ITU has a significant positive effect on the Actual Usage (AU) of mobile apps.

Table 1. 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.

(iii) SI has a significant positive impact on the PU of mobile applications.
(iv) PR has a significant and negative impact on the PU of mobile applications.
(v) PC has a significant and negative impact on the PU of mobile applications.
(vi) IA has a significant positive impact on the ITU of mobile applications.
(vii) IA has a significant positive impact on the AU of mobile apps.

METHODOLOGY

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) that enables the strength of the relationship between the dependent and independent variables to be successfully measured (Eisenhauer, 2009). The adopted model (TAM2) has the ability to successfully explain and predict the adoption of information technologies and also allows the inclusion of external variables which studies (Fathema, 2013; Tarhini et al., 2013) have shown to have a significant impact on technology adoption. The study proposes PU and ITU as the mediating variables which explain the relationship between the independent and dependent variables.

To answer the research questions and achieve the objectives of this study, primary data were used. A structured questionnaire was used to obtain data from farmers in the study area (Abia State). Data obtained covered farmers' demographics, attitude and behaviors (Dillman et al., 2016). The study survey instrument comprised two parts: the first part captures demographic characteristics of the farmers while the second part captures the measured variables on seven constructs which are presumed to have significant effects on the adoption of mobile applications by farmers. The measurement variables on the seven constructs were adopted from previous studies on the adoption of mobile applications (Malik et al., 2017; Lin, 2011; Sharma and Mishra, 2014; Al-Jabri and Sohail, 2012) and modified to suit this study (Figure 1).

Data collection

A cluster sampling technique was used in this study. Farmers in the study area were separated into three agricultural zones (clusters) (Table 1). Within each cluster, convenience sampling technique was used to sample farmers based on their attendance at extension meetings. The same standard questions were administered to all the farmers. The sampled farmers in the study area included livestock farmers, food crop farmers, poultry farmers and fish farmers. A total of 261 farmers were interviewed in the three agricultural zones in Abia State using a structured questionnaire, out of which 245 were valid and useful. Sixteen were rejected because they had incomplete answers. A combination of online surveys and paper questionnaires were used. The online survey was designed using Qualtrics and administered using an Android device with the guidance of the researcher and a research assistant.

Data analysis

Structural Equation Modelling (SEM) was used to analyze 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. The second process was to analyze the causal relationships among the constructs in the proposed model using SEM.

The EFA analysis was carried out using IBM® SPSS® software. Principal Component Analysis (PCA) extraction method was used with an Oblique rotation method. To ensure that the extracted factors were appropriate and reliable, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity were added in the factor analysis (Field, 2005). The KMO measure of sampling adequacy gave a result of 0.914 with Bartlett's test of sphericity highly significant at $p < 0.01$. This indicates that factor analysis is appropriate (Field, 2005). In factor extraction, SPSS identified 31 linear components within the data set. Seven of these components had eigenvalues greater than one, which explained the relatively large amount of variance (Hair et al., 2010; Kaiser, 1974). The total variance explained for the seven factors stood at 77.2%, which was above the 60% threshold considered as satisfactory by Hair et al. (2010) (Tables 2 and 3). 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.

Structural equation modelling (SEM)

The correlational relationships found in the CFA model were replaced with a structural model using the seven factors extracted during EFA. The structural model helped to simultaneously examine

Table 2. Principal component analysis.

Pattern matrix							
Variables	**Component**						
Variables	**Actual Usage**	**Perceived Usefulness**	**Intention To use**	**Information Awareness**	**Perceived Risk**	**Social Influence**	**Perceived Cost**
Actual Usage_2	0.95						
Actual Usage_4	0.94						
Actual Usage_1	0.91						
Actual Usage_3	0.91						
Actual Usage_5	0.9						
Actual Usage_6	0.89						
Actual Usage_7	0.88						
Perceived Usefulness_1		0.97					
Perceived Usefulness _2		0.95					
Perceived Usefulness _3		0.77					
Perceived Usefulness _5		0.75					
Perceived Usefulness _4		0.74					
Perceived Usefulness _6		0.72					
Intension to use_3			0.96				
Intention to use _2			0.85				
Intention to use _1			0.61				
Intention to use _5			0.6				
Intention to use _4			0.54				
Information awareness_2				0.93			
Information awareness _4				0.9			
Information awareness _3				0.88			
Information awareness _1				0.67			
Perceived Risk_4					0.86		
Perceived Risk_2					0.84		
Perceived Risk_3					0.84		
Social Inluence_2						0.82	
Social Influence_3						0.8	
Social Influence_1						0.66	
Perceived Cost_1							0.84
Perceived Cost_4							0.8
Perceived Cost_2							0.7

Extraction Method: Principal Component Analysis Rotation Method: Promax with Kaiser Normalization Rotation converged in 7 iterations.

Table 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

Table 4. 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. The estimation for regression weights of the hypothesized model regression weights: (Group number 1 – Default model).

			Estimate	S.E.	C.R.	P	Standardized coefficients
Perceived Usefulness	<---	Social Influence	1.284	0.1	12.816	***	0.803
Perceived Usefulness	<---	Perceived Risk	-0.175	0.071	-2.46	0.014	-0.137
Perceived Usefulness	<---	Perceived Cost	-0.394	0.09	-4.392	***	-0.304
Intention to Use	<---	Information Awareness	0.053	0.029	1.813	0.07	0.069
Intention to Use	<---	Perceived Usefulness	0.767	0.035	22.182	***	0.847
Actual Usage	<---	Information Awareness	0.796	0.117	6.781	***	0.41
Actual Usage	<---	Intention to Use	0.861	0.154	5.611	***	0.34

Significance levels: p<0.01***

the direct and indirect relationships between the constructs in the proposed model. It also helped to test the study hypotheses as well as test the model fit in comparison to the hypothesized structural model.

To successfully assess model fit, Hair et al. (2010) suggest using an acceptable goodness-of-fit index. 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: 672) maintained that Y^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 SEM model fit, as shown in Table 4, 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).

The SEM results from the estimation for regression weights of the hypothesized Model in Table 5 showed a significant relationship between the dependent and the independent variables in the research model. The seven proposed hypotheses in the structural model were supported (Table 6).

The structural model exhibited a strong explanatory power, which showed the extent to which the model explains variance in the data set (Figure 2). The exogenous variables SI, PR and PC accounted for 43% (R2 = 0.43) of the variance of Perceived Usefulness (PU) of mobile applications. PU and IA explained 79% (R2 = 0.79) of the variance of Intention to Use, while ITU and IA explained 46% (R2 = 0.46) of the variance of farmers' Actual Usage (AU) of mobile applications (Figure 2).

RESULTS AND DISCUSSION

The proposed extended TAM showed a high predictive ability in explaining the factors that influence the adoption of mobile applications by farmers. Based on previous studies on technology adoption (Kim et al., 2007; Malik et al., 2017; Wu and Wang, 2005), this study affirms the suitability of extended TAM in comprehending and explaining the mobile applications adoption behaviors 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 et al. (2012). In contrast, some studies found that SI did not have a significant effect on the Perceived Usefulness of some ICT (Arenas et al., 2015; Venkatesh et al., 2003). These researchers argued that SI is only crucial in a compulsory situation and especially in the early stages of experience when the opinions of the potential user are relatively unreliable. The importance of SI on PU in the smallholder context may be due to the close social connections between these farmers. As a result they judge the usefulness of mobile applications from other farmers in their network who are using the technology. They are more likely to be influenced by respected farmers who have adopted the technology and judge the usefulness by seeing the benefits they derive from the technology.

Perceived Risk (PR) had a significant negative effect on farmers' Perceived Usefulness (PU). This result is consistent with Kesharwani and Singh (2012) and Wu

Table 6. Hypotheses result testing.

Hypotheses	Path	Support	Regression weight
H1: SI has a significant and positive impact on the Perceived Usefulness of mobile applications	SI → PU	Yes	0.80***
H2: PR has a significant and negative impact on the Perceived Usefulness of mobile applications.	PR → PU	Yes	-0.14**
H3: PC has a significant and negative impact on the Perceived Usefulness of mobile applications.	PC → PU	Yes	-0.30***
H4: IA has a significant and positive impact on farmers' Intention to Use mobile applications	IA → ITU	Yes	0.07*
H5: IA has a significant and positive impact on the Actual Usage of mobile apps	IA → AU	Yes	0.41***
H6: PU has a significant and positive impact on a farmers' Intention to Use mobile applications.	PU → ITU	Yes	0.85***
H7: ITU has a significant and positive effect on Actual Usage of mobile apps	ITU → AU	Yes	0.34***

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

and Wang (2005), who found PR to have a negative impact on Perceived Usefulness of internet banking applications. This study showed that smallholders who had high levels of Perceived Risk (PR) consequently viewed mobile apps not to be useful and therefore had a negative Intention to Use (ITU) mobile apps. 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 the usage of mobile apps.

Perceived Cost (PC) also had a significant negative impact on the Perceived Usefulness (PU) of mobile applications. Similar studies on ICT adoption found PC to negatively affect Intention to Use (ITU) (Kim et al., 2007; Vassalos and Lim, 2016; Wu and Wang, 2005). According to Kim et al. the inclusion of cost prevents new customers from trying services they are not sure about. Cost is likely to be a large barrier to smallholders adopting new technology due to their low incomes. The impact of Social Influence (SI), Perceived Risk (PR) and Perceived Cost (PC) on the Perceived Usefulness (PU) provide considerable insight into the factors impacting Perceived Usefulness (PU) of agricultural mobile phone apps. These three exogenous variables explain 43% of the variation in Perceived Usefulness (PU). Firstly, this shows the influence that respected farming leaders adopting this technology can have on how other farmers perceive its usefulness. Secondly, both Perceived Cost (PC) and Perceived Risk (PR) can be significant barriers to smallholders' adoption.

Information awareness (IA) was the last exogenous variable that had a significant direct 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 et al. (1995) and Hakkak et al. (2013). According to Aker (2011: 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 uses of some of the available agricultural mobile applications. The strongest direct effect was from Information Awareness (IA) and Actual Usage (AU). This strong direct effect implies that most smallholders enjoying the benefits of mobile application were well informed about the usefulness of these mobile applications. Lack of information awareness affects intention to use and actual usage negatively. This signifies that information on the use of technology is necessary to enable the smallholder farmers to actually adopt the technology into their farming practices. Without this knowledge they may intend to use the technology but lack the understanding necessary to implement it.

Perceived Usefulness (PU) had a significant positive impact on farmers' Intention to Use (ITU) mobile applications. This variable acts as a mediating variable between SI, PC, PR and ITU. This implies that the effect of these variable affect the Intention to Use through the effect of Perceived Usefulness. This result is in accordance with previous studies e.g. (Hakkak et al., 2013; Kesharwani and Singh, 2012; Wu and Wang, 2005) which all found PU to have a significant positive impact on ITU of ICT. The highly significant level of this result suggests that smallholders were more motivated to use mobile apps because of their potential usefulness. The motivation to use comes from the positive impact of

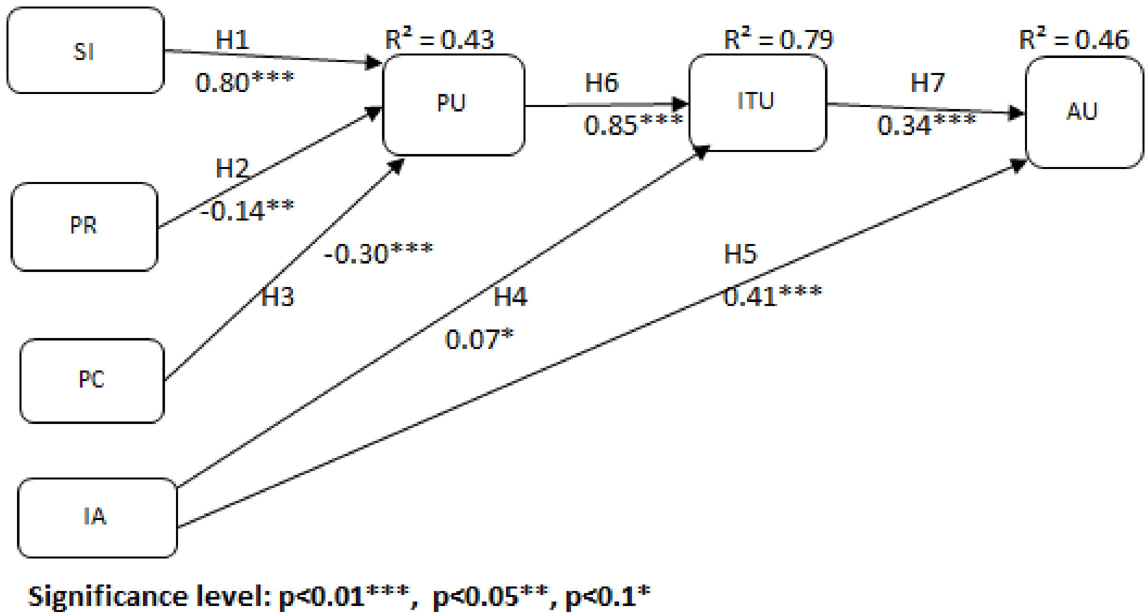

Figure 2. Empirical results of the structural model for factors affecting the adoption of mobile applications.

Social Influence (SI) on smallholder farmers, who have been influenced directly or indirectly that mobile applications are useful for their farming business. As a result, their Intention to Use (ITU) increases and this eventually leads to actual adoption of mobile applications. The last hypothesized 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 et al. (2015), Wu and Wang (2005) and Venkatesh et al. (2003), who all found a significant positive effect between behavioral intention to use and the actual usage/adoption of information communication technologies. The results indicate that if smallholders have strong intention to use mobile applications in their farming activities, then they are most likely to use them.

Conclusion

This research examined the factors that affect the uptake of mobile apps technology by farmers in Nigeria using SEM. SEM helped to analyze 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 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. However, internet connective which seems to have a significant influence on the adoption of ICT in developing countries did not stand out as a significant factor from the study's exploratory factor analysis. Instead the influence of internet connectivity was overlapped in perceived cost as farmers reported that they paid a high cost for data subscription. This potentially had a negative influence on farmers' intention to use and the actual adoption of mobile applications. The study demonstrates that extended TAM is a suitable model to explain the factors that influence mobile apps adoption for agricultural purposes. The study showed the level of importance of information awareness as a predictor of behavioral 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. The result of this study confirmed that information awareness is a key factor in the adoption of agricultural mobile applications. This study, therefore, lays a good theoretical foundation for other research using extended TAM (TAM2) to examine the impact of IA on the adoption of the ICT being studied. It also demonstrated the empirical applicability of extended TAM (TAM2) in studying technology acceptance in a developing country context such as Nigeria. The study helped to bridge the information gap between agricultural app developers and farmers by revealing the factors that affected the adoption and continuing use of mobile apps.

RECOMMENDATIONS

(i) More effort should be put into educating farmers on the usefulness of mobile apps.
(ii) App developers should put more effort in putting quality and useful content in the applications they develop for farmers.
(iii) App developers and other stakeholders such as financial institutions, government agencies and extension officers need to action to increase trust amongst the farmers.
(iv) Cost of internet subscriptions can be reduced or subsidized for farmers. This would encourage them to develop a positive intention towards the use of mobile apps.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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