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UNDERSTANDING FACTORS AFFECTING THE ADOPTION OF AGRI MOBILE APPS BY FARMERS FOR AGRICULTURAL INFORMATION MANAGEMENT: AN EMPIRICAL EVALUATION IN INDIA USING UTAUT2

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Abstract

The use of agriculture-based mobile applications can potentially help farmers to access information on crop management advisories, weather and climatic information, and access to the market. Unfortunately, due to a lack of adoption, many farmers have still yet to understand the potential advantages of this digital technology solutions. This study investigates the factors that affect farmers' adoption of agri-based mobile apps specific to information management. The study investigated the factors influencing the adoption of a mobile app for agricultural information management by conducting comprehensive survey among 600 farmers in Kerala, India's southern state, during 2021. A theoretical framework based on a unified theory of acceptance and use of technology2 (UTAUT2) was empirically evaluated using Structural Equation Modelling (SEM) to study the factors. The UTAUT2 model was extended with constructs Trust and Personal Innovativeness in IT were examined to understand better the farmers' adoption decisions. Data were analyzed using structural equation modelling (SEM) with the help of IBM SPSS and AMOS software. Reliability and validity of the proposed model have been tested. The results establish the general applicability of extended UTAUT2 model in context of mobile app adoption in Indian context with explanatory power of 69.9% and highlights the positive influence of performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), Habit (HA), Trust (TR), Hedonic Motivation (HM) and Personal Innovativeness in IT (IN) on mobile app adoption. It was also found that constructs Habit (HA), and Personal Innovativeness (IN) were shown to have a non-significant impact on the Usage. This research contributed to the existing of knowledge on farmer technology adoption. It demonstrates that the extended UTAUT2 model is fit for explaining the factors that influence mobile app adoption behavior. The findings are highly useful for agricultural extension practitioners and app designers who are developing digital agricultural solutions for the farmers.

Keywords: Agriculture, Farmers, SMART Phone, Mobile apps, structural equation modelling; agriculture information management, unified theory of acceptance and use of technology2, UTAUT2, India

1. Introduction

In today's digital world, smart mobile phones and handheld devices have become very important tools. Especially with the rise of digital services and mobile-based apps, people have adopted and made changes to many experiences through these devices (Singh et al., 2017, Agarwal et al., 2017). With the rise of smartphones and tablets, mobile collaboration in the end-user market allows for more flexibility and ubiquity for users, making it easier for them to get things done (Chhonker et al., 2017). The literature is becoming more and more interested in new digital technologies and mobile phone apps

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that can help farmers and growers manage their crops and farms (Gebbers, R, 2010). Farmers who use mobile phone technology will be able to get more relevant, timely, and accurate agricultural information (Jordan, R et al., 2016, Eitzinger, A et al., 2019). Data can be captured quickly and easily with smartphones and mobile devices, and it can be retrieved at any time, from wherever (Szilagyi & Herdon, 2006). Smartphones and other connected devices have made it easier and faster to get and send data. It helps to cut down on the time it takes to move data manually for information management or systems. The smart, intelligent, and connected devices keep the data transfer process error-free and allow people to directly input data through these apps on their phones (Deloitte, 2016). Crowdsourcing applications also help small and medium-sized farmers collect agricultural information in an efficient and effective way (Minet J et al., Beza, E et al., 2017). Farmers will be able to use smartphone apps to get the information and knowledge they need to make more informed decisions about how to increase agriculture production, protect their land resources, and improve their livelihoods (Chipidza W et al., Mittal, S, 2019).

1.1 Technology enabled Agri-information management

Agri-Information Management is a management process that involves the use of information and communication technology (ICT) to carry out farming or agricultural activities. Farming is done with the help of digital tools and solutions like computers and smartphones. These tools and solutions help farmers manage and monitor agricultural production, post-harvest activities, marketing, and access to price information. They also help farmers get inputs and seeds, as well as timely farm advice. In this case, geospatial, GIS, and remote-sensing technology can be used to get important information about farming activities from the ground up. The information about the land and its features helps farmers make decisions about how to plant crops, how to manage farm labour, and how to use capital and resources (Sani, Boadi, Oladokun & Kalusopa, 2014). Agricultural Information Management helps to manage agricultural resources by providing agricultural, scientific, commercial, and legal information about the different ways people grow food and land. It is common for Indian farmers to use ICT and advanced mobile-based devices and apps to manage farming activities such as managing crops or livestock or getting information about climate and weather conditions or getting information about the market. India's current agriculture market operations are mostly unorganized because there are a lot of intermediaries. Besides poor transportation, there aren't enough warehouses, people don't know about the market, and problems with infrastructure. Because of problems in the agriculture sector, farmers, growers, wholesalers, shippers, and retailers have problems with supply chain bottlenecks, insufficient irrigation facilities, lower agricultural productivity, and farmers who don't know how to use ICT. They also have a hard time finding enough workers (Kumar, 2019). However, with initiatives like Digital India, Skill India, Make in India, and Start-up India, changes have been made in the Indian agriculture sector. This has led to more people using mobile technology to manage their crops and farms. Different mobile and ICT projects have been launched in the agriculture sector in India, such as Dyandoot,

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Akshaya, e-sagu, Kissan Kerala, ITC e-Chaupal, Honeybee, Warana, and Praja. These projects are trying to change the way farmers do things.

1.2 The use of mobile apps by farmers in India.

Many Indian farmers are using mobile apps to improve their farming practises and set up an efficient system for keeping track of their agri-information. Farmers from many states use the Kisan Yojana mobile app to find out about different programmes that the government of India has set up for rural farmers. Weather, Market Prices, Plant Protection, Agro-advisory, Extreme Weather Alerts, Input suppliers, Soil nutrient information, Storage & Warehouses, Soil Labs, Veterinary Centre & Diagnostic labs, Crop Insurance and the Government scheme are among the mobile applications that have been developed to facilitate dissemination of information to farmers. The Pradhanmantri Kisan Samman Nidhi Yojana (PM Kisan App) is a smartphone app developed by Department of Agriculture and Farmers Welfare, Government of India and it has connected 15 million farmers so far and helps farmers availing the financial supports. Apps like Farm-o-Pedia and Bhuvan Hailstorm App have also been made by the Indian government to improve the way farmers do their work. This app is used by farmers in India so that they can get reliable farming information through the Farm-o-India app. The app was made by the Center for Development of Advanced Computing (C-DAC). It gives farmers real information about the health of their crops and the weather (Criyagen, 2016).

Apps like AgriMarket, Crop Insurance, Kheti-Badi, Krishi Gyan, and IFFCO Kisan Agriculture are also being made by non-government and private sector groups in India to help farmers. They want to improve farming culture in the country. To help farmers make smart farming decisions, the Indian Farmers' Fertilizer Cooperative Ltd. (IFFCO) has launched an app called IFFCO-Kisan Agriculture. This app helps farmers make smart decisions about farming. Many different types of information about farming can be found on this app, from audio and text to images and videos: agricultural advisories and market prices to pest control and the weather. The farmers can use this app to get this information in a variety of ways. It has information in a lot of different languages, which makes it easier for farmers to get the information they need and put it in their agriculture profiles.

Crop Insurance is another app that farmers use. The farmers can use the app to figure out how much insurance they'll have to pay for their crops. It also gives them information about the cut-off dates for different company contacts and contracts. By using the app, you can get a lot of information about how much your crop is insured for, how much it costs, and how much of a subsidy it gets. It also gives farmers a bigger way to connect with stakeholders, insurance companies, banking organisations, and other groups in the agriculture community. The Agri Media video app is one of the newest and most cutting-edge apps that farmers in India use to stay up to date on the different technologies that are used for farming. Getting information about retail farming, the amount of food that's grown, how it's made, how it's delivered, and how it's sold after its grown are all important parts of this. Users can talk to farm experts directly through this app and get help with their questions. The farmers can upload pictures of their farms and get information about

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how to increase their yield or get rid of pests from crops that have been infected. The video conferencing feature in this app allows farmers to meet together, talk about agendas, and look at new technology adoptions in rural farming. On the other hand, when farmers use the FarmBee-RML Farmer mobile app, they get reliable information about the fertility of the soil, different stages of the crop life cycle, and 450 different types of crops. There are 1300 markets and 3500 weather stations on the app that farmers can use to figure out how much their crops should sell for. Plantix (*Tibbets, 2018.* Agus et al, 2017*)* is a crop protection advisory app for farmers, extension workers, and gardeners on their smartphones. Plantix was created by GmbH, one of the Berlin based Startup Company. The app claims to be able to diagnose pest infestation, plant diseases, and nutritional deficiencies in crops, and also provide control measures. Farmers can also have access to the local weather information, agricultural guidance throughout the season, and disease alerts if a disease is emerging in particular area.

Another app called Mandi trade is used by farmers who don't read very well to get information about crop prices from the government in an audiovisual format. It lets farmers who live in far-off places see government notices about different types of crops. RainbowAgri is also used by farmers in rural and remote areas to connect with local buyers and sellers. The mPower Social mobile app is used by cattle owners and people who raise cattle to get information about cattle and connect with vets who can help them. This app lets farmers, people who work with animals, people who work with dairy, and people who work with fish use it to get the message they need to do their jobs well. So, it can be said that in the last few years, mobile apps have become very important for the agriculture industry and its members because they allow everyone to get access to a lot of information, make smart decisions, and manage a lot of agri-information in a very efficient way.

The use of mobile apps for farming has led to a rise in smartphone use in rural farming areas. This has encouraged farmers to use m-commerce models to do agriculture work. People are more likely to use mobile apps for farming, animal husbandry, dairy, and fisheries because they help them do their jobs better. For example, farmers use apps like Ah Ph.D. harvest loss, Ag Ph.D. planting population, and Fertilizer calculator to figure out how much money they will make and lose from their crops before they plant them. When farmers use mobile apps like Ah Ph.D. harvest loss, they can figure out how much wheat, maize, oat, barley, and soybean yields will be lost per acre before they start harvesting. This is done before the farmer starts harvesting. By using this app, you can figure out how much money you'll lose in crops and how much money you'll lose in crops. It lets farmers decide how much they want to charge for their crops so that they don't lose money and make a lot of money off of what they make on their farms (Kaur, Sharma & Mohan, 2020).

The development of farm management information systems (FMIS) has been the focus of recent scientific research. These systems help farmers make good decisions on a daily basis. There are only a few studies that look at how farmers use mobile apps to keep track of their data and information because this has only been a hot topic in the last six years. These agri based mobile apps might be really useful. They can help the farmers in

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making smart decisions on how to manage with radical changes, address the challenges of future increased food demand, increase efficiency, and decrease farming's environmental impact. Despite the fact that there are numerous reasons why farmers should use mobile applications, they are not widely adopted. As a result, the factors which influence farmers' adoption of mobile apps to help them manage their information and data are examined in this study to discover if any exist.

Several studies have looked at how farmers in African countries use smartphone apps, but only a few have looked at how Indian farmers use them. While many studies have looked at farmers' general willingness to use smartphone apps, none have looked at farmers' intentions to use smartphone applications in developing countries (Jordan, R, 2016). As a result, we looked into the reasons why farmers in India don't use mobile apps to keep track of their agricultural information.

2. Theoretical Model of Research

The unified theory of acceptance and use of technology2 (UTAUT2), which aims to explain factors like people's intents to use a mobile phone app, served as the theoretical underpinning for this study (Venkatesh et al., 2003). This theory has been proven and has been empirically validated in a wide range of fields (Williams, M.D, 2015). The proposed model, which is based on UTAUT2, was later extended by adding two constructs Trust(TR) and and Personal Innovativeness in IT (IN). The proposed Research Model and hypothesis regarding how the factors of farmers' behavioural intention (BI) can be associated are shown in Figure 1.

This study integrates additional factors and relations to Venkatesh et al (Venkatesh,.'S Thong, and Xu, 2012) unified theory of acceptance and use of technology2 (UTAUT2) to obtain a greater understanding of farmers' first adoption choice. UTAUT 2 was developed with consumer in mind. The behavioral aspects of "performance expectancy" (PE), "effort expectancy" (EE), "social influence" (SI), "facilitating conditions" (FC), "habit" (HA), and "hedonic motivation" (HM) were the most important constructs. Two new constructs have been added to the model: trust (TR) and personal innovativeness in IT (IN). The research was carried out in Kerala, India's southernmost state, in 2021 with 600 farmers from Kerala's five agro-ecological zones. Agro-ecological zones (AEZs) are physiographic-based spatial classifications. In the state, five agro-ecological zones (AEZs) have been established. (KM Nair et al, 2013). Figure 2 shows the distribution of the state's agro-ecological zones.

Constructs used for the study

Performance Expectancy (PE)

Performance Expectancy is defined as "the degree to which an individual believes that u sing the system will help him/her attain gains in job performance," according to the Unifi ed Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al.,2003). Perf ormance Expectancy, the strongest predictor of intention to use technology which is sig nificant in both forced and voluntary contexts. PE's impact on system usage in a consu mer scenario has been reaffirmed by Venkatesh et al. (2012).in this context, PE is descr

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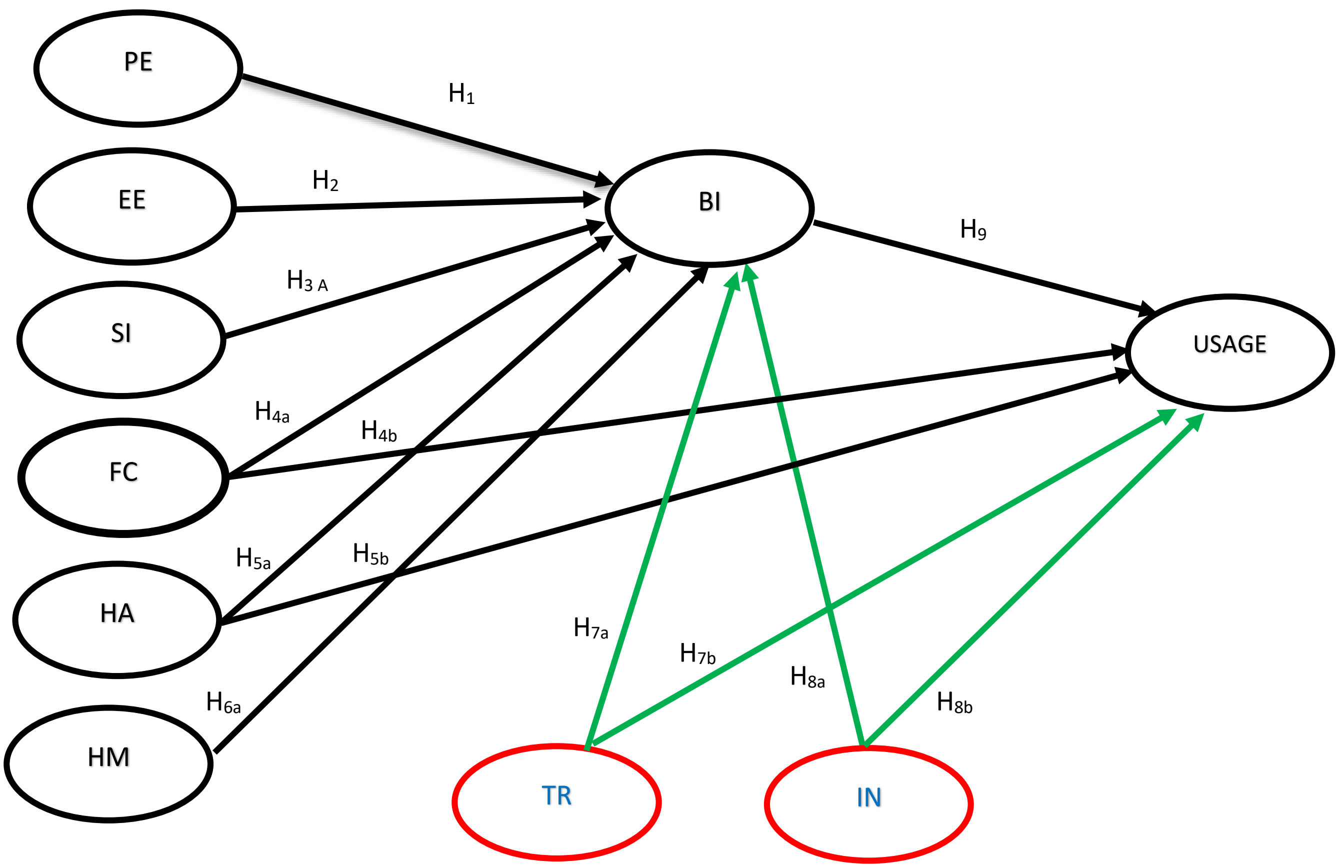
ibed as "the extent to which use of a technology will aid farmers in executingspecific acti vities." One of the most compelling advantages of a mobile agriculture app is its capability to give farmers with easy access to all relevant information at the right time, in the right place, and in the right context.

Figure 1 : Research model: Adapted from the Extended UTAUT2 Model. Source: Venkatesh et al (2012).



(PE- Performance Expectancy, EE-Effort expectancy, SI-Social Influence, FC-Facilitating Conditions, HA-Habit, HM- Hedonic Motivation, TR-Trust, IN- Innovativeness, BI-Behavioural Intention)

Therefore, we hypothesized that:

Hypothesis 1 (H1). Performance expectancy (PE) positively affects behavioral intention (BI) to use mobile phone app by farmers for agricultural information management

Effort Expectancy (EE)

"The degree of convenience associated with the use of the system," says Effort Expecta ncy (Venkatesh et al, 2003).When they introduced UTAUT2, Venkatesh et al. (2012) has redefined EE in the context of consumer use as "the degree of easiness connected with consumers' use of technology." The majority of UTAUT and UTAUT2 studies show

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that EE has a considerable impact on the desire to employ various technologies and sys tems (Lian, 2015; Martins et al.,2014; Oye et al. 2011). In the case of agricultural mobile apps, certain farmers may be more literate in ICTbased technologies than others, and h ence should have fewer difficulties utilising a mobile phone to obtain agricultural informa tion. Farmers are more likely to adopt a mobile application if they can easily find and analyse relevant data. As a result, we hypothesised that:

Hypothesis 2 (H2). Effort expectancy (EF) positively affects behavioral intention (BI) to use mobile phone app by farmers for agricultural information management

Social Influence (SI)

“The degree to which individual believes important others believe he or she should use the new system,” according to the definition of Social Influence (Venkatesh et al.,2003).

SI is a direct determinant of behavioural intention, according to Venkatesh et al. (2003). "social influence" refers to the amount that farmers believe important people believe that they should adopt a specific technology, such as a mobile application. (Venkatesh; and Thong; Xu, 2012). When it comes to new technology, people consult their social network connections, particularly their friends and relatives, and are influenced by social pressure to perform from those who matter to them. Therefore, we hypothesized that:

Hypothesis 3 (H3). Social influence (SI) positively affects behavioral intention (BI) to use mobile phone app by farmers for agricultural information management

Facilitating conditions (FC)

"Facilitating conditions" refer to an individual's perception of an organisational and technical infrastructure that exists to ensure that the system is easier to operate (Venkateshet al., 2003).

Venkatesh et al. (2003) claim that when Performance Expectancy and Effort Expectanc y are present, Facilitating Conditions become insignificant in determining intention. As a result, in UTAUT, Facilitating Condition is portrayed as a direct antecedent of usage. Venkatesh et al. (2012), on the other hand, incorporated a direct link between Facilitating Conditions and Behavioural Intention when they applied UTAUT2 to the consumer environment.

The reason for this is because many Facilitating Conditions elements will be freely available within the organizational setting, but not in the consumer situation. To use a mobile app, user has to be able to operate the smart phone, acquire and install the app and navigate the information or content.

Therefore, we hypothesized that:

Hypothesis 4 (H4a). Facilitating conditions (FC) positively affect behavioral intention (BI) to use mobile phone app by farmers for agricultural information management

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Hypothesis 4 (H4b). Facilitating conditions (FC) positively affect USAGE (U) of mobile phone app by farmers for agricultural information management

Habit (HA)

Habit is defined by Limayem et al.(2007) as "the extent which persons tend to perform behaviors automatically because of learning'.

According to Ajzen and Fishbein (2000), frequent repetition of a behaviour can lead to t he creation of attitudes, which can then induce intentions. In the formation of a habit, tim e is also a component. Several empirical research have been conducted in order to und erstand the major impact of habit on technology usage.

Therefore, the following hypotheses is formed in tune with that of Venkatesh et al. (2012)

Hypothesis 5 (H5a). Habit (HA) positively affect behavioral intention (BI) to use mobile phone app by farmers for agricultural information management

Hypothesis 5 (H5b). Habit (HA) positively affect USAGE (U) of mobile phone app by farmers for agricultural information management

Hedonic Motivation (HM)

In UTAUT2, hedonic motivation is a positive predictor of consumer behaviors intention to use technology.

The fun or pleasure received from employing a technology is known as hedonic motivati on (Venkatesh et al.,2012). Hedonic motivation, according to Brown and Venkatesh (20 05), is defined as the delight or happiness derived from the use of technology. The more the entertainment value provided by mobile apps, the more farmers will be willing to utili se mobile apps.

As a result, we came up with the following hypothesis:

Hypothesis 6 (H6). Hedonic Motivation (HM) positively affect behavioral intention (BI) to use mobile phone app by farmers for agricultural information management

Additional Constructs investigated

In addition to the current UTAUT2 paradigm, Trust (TR) and Personal innovativeness in IT (IN) were included as new constructs.

TRUST (TR)

The trust (TR) construct was intended to look into to the role of extension officers (as information suppliers and developers of app content and technology) and the facilitator of app usage. Despite the fact that trust is a subjective notion, it has garnered attention in the context of UTAUT and mobile payments, which were investigated alongside risk (Baganzi, R, 2017). Unlike Beza (Beza, E et al, 2018), this study focused on trust in the app service provider and the information provided through the app and the service provider rather than technology trust.

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Trust is defined as the degree to which the mobile-phone app provider(s) or agricultural extension worker is believed to really want to help the farmer for reasons other than self-interest. The majority of smallholder farmers rely on agriculture, and their able to converse agricultural advice and crop management information via mobile apps is highly dependent on the trust worthiness of information service providers and agencies (e.g., extension worker, researchers, and research institutes). Farmers want to avoid using any technology that could make their farming operations more unreliable and unsafe. Therefore, we hypothesized that:

Hypothesis 7 (H7a). Trust (TR) positively affect behavioral intention (BI) to use mobile phone app by farmers for agricultural information management

Hypothesis 7 (H7b). Trust (TR) positively affect USAGE (U) of mobile phone app by farmers for agricultural information management

Personal Innovativeness in Information Technology (IN)

Agarwal and Prasad (1998) defined personal innovativeness as "the willingness of an individual to try out any new information technology," based on Rogers' innovation diffusion theory (Rogers, 1962). As a result, someone who has a great desire to learn about and experiment with new systems and technologies will have a high level of innovativeness and a desire for novelty (Slade et al., 2015). Because personal features and individual differences have such a large impact on the adoption process, marketers and practitioners must consider the concept of user innovativeness (Aroean and Michaelidou, 2014). Existing literature on technology adoption has established personal inventiveness as a critical motivator of purchasing and adopting new things and technological breakthroughs in a variety of industries (Koivisto et al., 2016). Personal innovativeness has a major impact on behavioural intentions to adopt technology in a range of domains, including social networking sites (Wijesundara and Xixiang, 2017) and online purchase intentions, according to existing research (Juaneda-Ayensa et al., 2016; Escobar-Rodrguez and Carvajal-Trujillo, 2014). The higher one's personal innovativeness, the greater one's drive to adopt new technology, it is believed (Kuo and Yen, 2009). Furthermore, highly innovative people have been shown to actively seek out information about new technologies or ideas using a variety of technological channels. They are more likely to accept new technology because they can live with a lot of ambiguity (Rogers, E.M 2002). As a result, we arrive to the following hypothesis:

Hypothesis 8 (H8a). Personal Innovativeness (IN) positively affect behavioral intention (BI) to use mobile phone app by farmers for agricultural information management

Hypothesis 8 (H8b). Personal Innovativeness (IN) positively affect USAGE (U) of mobile phone app by farmers for agricultural information management

3. Materials and Methods

3.1. Research Study Area and Context

The research was carried out in Kerala, India's southernmost state, which has 14 districts and is divided into five agro-ecological zones. Agro-ecological zones are wide geographic

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classifications based on physiographic characteristics. (FAO1978). Five agro-ecological zones (AEZs) have been established in the state.

The spatial distribution of the state's agro-ecological zones is depicted in Figure 2.

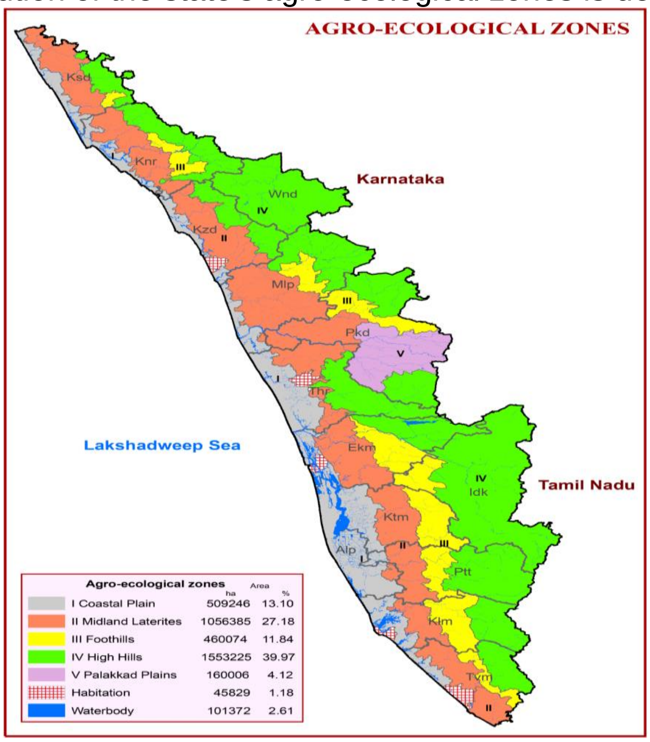

Figure. 2 The study area- 5 Agro-ecological Zones of Kerala. (Source : KM Nair et al, 2013)

3.2. Data Collection, Sampling, and Measurement Tool

The data was gathered through a comprehensive survey performed in late 2021 with farmers in the region, which included both face-to-face and online interviews. The target population of the study was the f armers who have formally registered with the Department of Agriculture and Farmers Welfare, Government of Kerala, who are using a wide range of agricultural extension and welfare services make up the study's respondents. The respondents were chosen using a multi-stage stratified random sample procedure. The participants were chosen in two stages. The Agro Ecological Zones were included in the first stage, and the respondents who were associated to the zone were chosen at random from the database in the second stage. These 5 agro ecological zones resulting in a total of 600 responses, with no missing values.

Standard questions were used to survey the farmers based on (Beza et al 2018) and Venkatesh (2012 , with sections covering basic information and demographic information, their experience using mobile applications to acquire agricultural information and advisories, and questions about the constructs model. The question was introduced with a statement that the questions were about the potential use of a mobile phone app to acquire agricultural information.

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According to Hair, each construct must have three to five components (Hair, J.F 2014). In the framework of an agriculture information based mobile app, a total of 30 measuring questions were carefully constructed, with response options ranging from "Totally disagree" (1) to "Totally agree" (5) on a five-point Likert scale. The survey was pilot tested with 50 farmers ahead of time.

3.3. Data Analysis and Estimation Techniques

SPSS Statistics Version 26 and AMOS Version 28 were used to conduct statistical analysis. The descriptive statistics were used to assess the demographic data first. The model described in Figure 2 was then sorely tested using structural equation modelling (SEM). SEM was chosen because it allows for the simultaneous analysis of all relationships, combining multiple regression and factor analysis, as well as the examination of both observable and latent variables (Hair, J.F et al, 2014).

To test the reliability and validity of our measurement model, researchers employed maximum likelihood estimation to undertake a confirmatory factor analysis (CFA). Second, we looked at the path analysis of the structural model estimates to see if our hypotheses and the proposed model's prediction items were valid. Common method variance (CMV) and multi collinearity were investigated prior to analyzing the measurement and structural models. All factor(s) accounted for approximately 50% of the variance, according to the data. The Harman single-factor test was used iteratively in SPSS to check for a typical technique bias. The measurement model has been validated for (a) concept reliability, (b) indicator reliability, (c) convergence validity, and (d) discriminant validity prior to the path analysis (hypotheses-testing). Composite reliability (CR) and Cronbach's alpha values were also used to test construct reliability, which is a measure of the assessment items' internal consistency (Hair, J.F et al, 2014). The indicator's dependability was tested using factor loadings. Convergent validation investigates if items accurately reflect their associated construct (that is, whether they converge on the target construct), whereas discriminant validity investigates whether two constructs are statistically and theoretically distinct (Hair, J.F et al, 2014). The criterion for assessing convergent validity was the average variance extracted (AVE) (Fornell, C 1981). The heterotrait-monotrait ratio (HTMT) was calculated using SPSS to assess discriminant validity.

4. Results and Discussion

4.1. Descriptive Statistics

Table 1. shows the demographic characteristics of the farmers surveyed for this study. Most respondents were male (73.5%), and female (26.5 %). (49.5%) of the respondents were between age 30-40, (26.5 %) of the respondents were between age 20-30, (13.3%) of the respondents were between age 40-50, (6.7%) of the respondents were above 50 years of age and (4%) of the respondents were below 20 years of age.

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Table 1. Demographic characteristics of the farmers

Gender-wise classification of respondents			
Sl.No	Factor	Frequency(600)	Percentage
1	Male	441	73.5
2	Female	159	26.5
Age-wise classification of Respondents			
Sl.No	Factor	Frequency(600)	Percentage
1	Below 20 years	24	4.0
2	20-30 years	159	26.5
3	30-40 years	297	49.5
4	40-50 years	80	13.3
5	Above 50 years	40	6.7
Education level classification of Respondents			
Sl.No	Factor	Frequency (600)	Percentage
1	Below 12th	148	24.7
2	Equivalent 12th	158	26.3
3	Graduate	225	37.5
4	Post graduate	48	8.0
5	Professional Degree	21	3.5
Farming Experience level classification of respondents			
Sl.No	Factor	Frequency(600)	Percentage
1	Upto 10 years	320	53.3
2	10-20 years	235	39.2
3	20-30 years	37	6.2
4	Above 30 years	8	1.3
Classification of Respondents based on type of farming activities involved			
Sl.No	Factor	Frequency (600)	Percentage
1	Agriculture (Crops)	278	46.3
2	Diary & Animal Husbandry	70	11.7
3	Fisheries	34	5.7
4	All types	218	36.3

4.2. Evaluation of the Measurement Model

The measurement model's first fit, which included all of the construction's features, was adequate. The model fit indices indicated a "good measurement model" with the following index values: CMIN/DF: 1.190; CFI: 0.999; and RMSEA: 0.018 (Hair, J.F. et al., 2014). (See Table 2) Table 3 shows the results of (i) construct reliability, (ii) indicator reliability, (iii) convergence validity, and (iv) discriminant validity measurement model assessments.

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All of the constructs achieved composite reliability (CR) and Cronbach's alpha values more than 0.7, confirming that the construct's reliability requirement was met (Hair, J.F et al, 2014). All factor loadings were more than 0.7, indicating that the instrument has high indicator reliability (Table 3). Due to the minimal factor loading, no items had to be deleted. The average variance extracted (AVE) value (Fornell, C, 1981) is used to assess convergence validity, and all of the constructs had an AVE greater than the minimum permissible limit of 0.5, indicating that the convergence validity requirement was met.

Table 2. Summary of fit indices for the measurement and structural models

Model Fit Indices	Recommended Value	Model Results	Reference
Normed chi-square (CMIN/DF)	< 3	2.069	Hair, J.F et al, (2014) Hu, L.-T. et al (2009)
Comparative fit index (CFI)	Above 0.92 or 0.94	0.933	Hair, J.F et al, (2014) Hu, L.-T. et al (2009)
TLI (Tucker–Lewis index)	Above 0.92 or 0.94	0.924	Hair, J.F et al, (2014)
Root mean square error of approximation (RMSEA)	Value < 0.08 (with CFI of 0.92)	0.042	Hair, J.F et al, (2014) Hu, L.-T. et al (2009)

Table 3: Summary of reliability and validity measures of the measurement model.

Construct	Number of items	Composite Reliability (CR)	Cronbach's Alpha	AVE	Factor Loadings
PE	4	0.811	.811	0.518	0.705 - 0.753
EE	4	0.860	.855	0.608	0.643 – 0.860
SI	4	0.897	.895	0.689	0.653 – 0.924
FC	4	0.813	.795	0.524	0.569 – 0.797
HM	3	0.768	.768	0.525	0.714 – 0.738
HA	3	0.716	.713	0.511	0.683 – 0.811
TR	4	0.817	.816	0.528	0.774 – 0.805
IN	3	0.764	.754	0.521	0.673- 0.800
BI	3	0.905	.900	0.762	0.761 – 0.930
U	7	0.802	.787	0.575	0. 715 – 0.794

The data in Table 4, where the matrix indicates the HTMT values between each pair of components, which were all below 0.9, can be used to derive discriminant validity. The result demonstrates strong indicator and construct reliability, along with good convergence and discriminant validity, implying that the constructs were statistically distinct and could be used to assess the structural model's path analysis.

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Table 4: Matrix showing the discriminant validity

Constructs	HA	PE	EE	SI	FC	TR	HM	IN	BI	USAGE
HA	**0.677**									
PE	0.006	**0.720**								
EE	0.007	-0.204	**0.780**							
SI	-0.022	0.284	-0.100	**0.830**						
FC	0.004	0.284	-0.141	0.587	**0.724**					
TR	0.003	0.392	-0.303	0.361	0.446	**0.727**				
HM	0.173	-0.019	0.102	-0.031	-0.051	-0.042	**0.725**			
IN	0.249	0.034	0.037	-0.026	-0.057	0.059	0.141	**0.722**		
BI	-0.007	0.080	-0.112	0.465	0.561	0.221	0.095	0.089	**0.873**	
Usage	0.077	0.003	0.025	0.051	-0.015	0.077	0.050	0.137	0.193	**0.758**

4.3. Results of Path Analysis Estimation

The structural equation model (path analysis) was assessed once the measurement model was validated. The overall model fit was good for the structural model (Table 2). The path analysis showed eight hypotheses that were confirmed (Table 5). Performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) all demonstrated significant positive effects on behavioural intention (BI) (confirming H4). Facilitating Conditions (FC) (confirming H4b), Habit (HA) (confirming H5b), Trust (TR) (confirming H7b), and Personal Innovativeness (IN) all found to have positive effects on Usage (USAGE) (confirming H8b).

Apart from the UTAUT2 core constructs, the new contructs like Trust (TR) (H7b) and Personal Innovativeness (IN) (H8b) constructs had a significant impact on the USAGE of the mobile-phone app, implying that trust in the extension service provider and the quality of the mobile app's information may assist them in using the app. Farmers also believed that their own personal inventiveness would aid them in using the app, exploring new more features and gain a better understanding of farm management and best farming practices.

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Table 5. Summary of the results of the path analysis of the structural model.

Hypothesis	Structural Path	Estimates	P Value	Result
H_1	PE ---> BI	-.133	***	Supported
H_2	EE ---> BI	-.124	.003	Supported
H_3	SI ---> BI	.279	***	Supported
H_4a	FC ---> BI	.865	***	Supported
H_4b	FC ---> U	-.244	***	Supported
H_5a	HA ---> BI	-.194	.012	Supported
H_5b	HA ---> U	.096	.072	Not Supported
H_6	HM ---> BI	.292	***	Supported
H_7a	TR ---> BI	-.107	.007	Supported
H_7b	TR ---> U	.084	***	Supported
H_8a	IN ---> BI	.314	***	Supported
H_8b	IN ---> U	.083	.061	Not Supported
H_9	BI --> U	.199	***	Supported

5. Results and Discussions

The findings of a relation between performance expectancy and behavioral intention (H1) is consistent with earlier mobile banking research (Baptista, G, 2015 and Oliveira, T et al, 2014). Farmers' intentions to use mobile-based communication technologies for agricultural information (Engotoit, B et al 2016), decision support tools (Rose et al 2016), precision agriculture (D'Antoni et al., 2012; Adrian et al., 2005), dairy farming technology (Flett et al., 2004), and SMS agricultural advice are influenced by their performance expectations (Beza, E et al 2018). Farmers' intentions to use apps will be strengthened if they believe that mobile apps will improve their daily agricultural performance.

Effort Expectancy (EE) was found to have a positive relationship with behavioral intention (H2). This demonstrates that farmers believe that using mobile apps needs little effort. The findings also show that mastering the many functionalities offered by these mobile applications is simple and straightforward. Other research has found consistent outcomes in consumer SMS adoption (Kim et al., 2008), farmer adoption of decision support systems (Rose et al., 2016), and precision agriculture adoption (Rose et al., 2016). (Aubert et al., 2012).

Social Influence appears to have a considerable impact on Behavioural Intention, according to the data (H3). This result is in line with the UTAUT2 model's initial prediction. (Venkatesh and colleagues, 2012). According to the findings, social influence is a crucial role in the decision to continue using mobile applications in agriculture. Friends and relatives who encourage farmers to use these mobile apps have an impact.

Facilitating Conditions have a significant impact on behavioral intention and Usage (H4a) and (H4b). This result matches that of the original UTAUT2 model (Venkatesh et al.,2012). The findings show that Facilitating Conditions is the strongest predictor of the intention to continue using mobile applications. Farmers have been inspired and influenced to adopt mobile apps as a result of enabling factors such as technology infrastructure capabilities and extension staff assistance. According to the data, the most important predictors of mobile app adoption are Facilitating Conditions. Due to enabling factors like as technological capabilities, reliable network connection, and assistance from others, farmers have been inspired and encouraged to adopt and use mobile apps.

Behavioural Intention appears to be influenced by habit (H5a). This result is in line with the UTAUT2 model's initial prediction. (Venkatesh and colleagues, 2012). According to the findings, habit is a significant factor in the decision to continue using mobile applications in agriculture. Farmers are accustomed to using mobile apps to obtain agricultural information. The findings (Table 5) show that farmers' habits have a favorable impact on mobile app usage (H5b). It means that farmers have made using these apps a habit, and it is now part of their daily routine.

Hedonic Motivation has a considerable impact on Behavioural Intention, according to the findings (H6). This result is in line with the UTAUT2 model's initial prediction. (Venkatesh and colleagues, 2012). It demonstrates that farmers use the mobile app for entertainment, amusement, and pleasure.

Trust has a considerable impact on Behavioural Intention (H7a) and Usage, according to the results (H7b). It is consistent with previous research. Farmers think that information reliability and trustworthiness, and also trust in the expert service provider, have become increasingly vital.

Personal Innovativeness in IT has a considerable impact on Behavioural Intention, according to the findings (Table 5). (H8a). This result is in consistent with the findings of other investigations. Farmers' innovative skills, exploration, and aspiration for new technologies are all crucial factors in adopting mobile apps, according to the findings. Personal Innovativeness, on the other hand, appears to have a negative relationship with Usage (H8b).

The results (Table 5) demonstrate that the hypothesized links between habit (H5b) and personal IT innovation (H8b) were not confirmed and did not significantly predict mobile app usage (U). Farmers' lack of habit can be attributed to the fact that they have never adopted mobile apps for agricultural information management before, therefore it is not yet their habit. As shown by the low importance of Personal Innovativeness, farmers do not enjoy and found innovation and the ability to explore new technology.

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6. Implications and Limitations

6.1. Implications

The UTAUT2 framework and doing a SEM analysis were seen to be effective techniques to learn more about farmers' mobile app adoption decisions in this study. Among the factors examined, the strongest predictors of farmers' intention to utilise mobile apps for agricultural information management were performance expectancy, effort expectancy, social influence, and facilitating conditions. Farmers' usage of mobile apps is influenced by a variety of factors, including habit, trust, and personal innovativeness. The group's hedonic motivation seems to be of no significance.

The rapid advancement of mobile technologies has influenced the creation and use of mobile applications. As a consequence, researchers can adapt and extend existing adoption models such as the UTAUT2 even while integrating socio-psychological measures. Given that farmers' behavioural intention to adopt mobile apps has been significantly predicted by performance expectancy, effort expectancy, social influence, and facilitating conditions, app providers could ensure that the app provides value-added features and benefits to farmers, and also the necessary technical infrastructure is available to help them in using it.

6.2. Limitations

Despite its benefits to elements that are important for farmers to adopt a mobile application to offer information on agriculture, there are certain limits to consider. To begin with, the factors that influence technology adoption varied by place, therefore testing the model's validity with farmers from various cultures in both the developed and developing worlds would be both theoretical and practical. Another point to consider is that our findings are exclusive to Kerala, India's southernmost state, and the situation in other locations with lower digital literacy or smartphone use may differ dramatically. As a result, when applying the findings to other regions with diverse technological infrastructures, caution must be exercised.

7. Conclusion

Farmers can benefit from the advantages of acquiring the right information at the right time while also contributing to farmer-centric applications that encourage sustainable agrarian intensification by using agricultural-based mobile applications. There has been limited research on the uptake of agricultural apps across the Indian subcontinent. This study used the UTAUT2 framework to identify the primary behavioral characteristics of farmers' intentions to use agriculture applications in India. This highlights the need of understand farmers' perspectives on benefits. As a result, extension personnel and government agencies proposing implementing mobile phone apps must ensure that the information they give is beneficial to farmers.

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References

1. Agarwal, R. and Prasad, J. (1998), "A conceptual and operational definition of personal innovativeness in the domain of information technology", Information Systems Research, Vol. 9 No. 2, pp. 204-215
2. Baganzi, R.; Lau, A.K.W. (2017). Examining Trust and Risk in Mobile Money Acceptance in Uganda. Sustainability, 9, 2233
3. Baptista, G.; Oliveira, T. (2015). Understanding mobile banking: The unified theory of acceptance and use of technology combined with cultural moderators. Comput. Hum. Behav. 50, 418–430.
4. Beza, E.; Reidsma, P.; Poortvliet, P.M.; Belay, M.M.; Bijen, B.S.; Kooistra, L. (2018). Exploring farmers' intentions to adopt mobile Short Message Service (SMS) for citizen science in agriculture. Comput. Electron. Agric.,151, 295–310
5. Beza, E.; Steinke, J.; Van Etten, J.; Reidsma, P.; Fadda, C.; Mittra, S.; Mathur, P.; Kooistra, L. (2017). What are the prospects for citizen science in agriculture? Evidence from three continents on motivation and mobile telephone use of resource-poor farmers. PLoS ONE, 12, e0175700
6. Chhonker, M.S., Verma, D. and Kar, A.K. (2017), "Review of technology adoption frameworks in mobile commerce", Procedia Computer Science, Vol. 122, pp. 888-895.
7. Chipidza, W.; Leidner, D.(2019). A review of the ICT-enabled development literature: Towards a power parity theory of ICT4D.J. Strateg. Inf. Syst, 28, 145–174.
8. Criyagen (2016). Criyagen Solutions For Sustainable Agriculture. Retrieved February 14, from http://criyagen.com/blog/
9. Eitzinger, A.; Cock, J.; Atzmanstorfer, K.; Binder, C.R.; Läderach, P.; Bonilla-Findji, O.; Bartling, M.; Mwongera, C.; Zurita, L.; Jarvis, A.(2019). GeoFarmer: A monitoring and feedback system for agricultural development projects. Comput. Electron. Agric, 158, 109–121.
10. Emeana, E.M.; Trenchard, L.; Dehnen-Schmutz, K. (2020). The revolution of mobile phone-enabled services for agricultural development (m-Agri services) in Africa: The challenges for sustainability. Sustainability, 12, 485.
11. Engotoit, B.; Kituyi, G.M.; Moya, M.B.(2016). Influence of performance expectancy on commercial farmers' intention to use mobile-based communication technologies for agricultural market information dissemination in Uganda. J. Syst. Inf. Technol., 18, 346–363.
12. Fornell, C.; Larcker, D.F(1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. J. Mark. Res., 18, 39–50
13. Fornell, C.; Larcker, D.F.(1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. J. Mark. Res., 18, 39–50
14. Gebbers, R.; Adamchuk, V.I. Precision Agriculture and Food Security. Science 2010, 327, 828–831.
15. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E.(2014), Multivariate Data Analysis, 7th ed.; Pearson Educated Limited: New York, NY, USA, ISBN 978-1-292-02190-4.
16. Hu, L.-T.; Bentler, P.M.(2009), Structural Equation Modeling: A Multidisciplinary Journal Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Multidiscip. J, 6, 1–55.
17. Jordan, R.; Eudoxie, G.; Maharaj, K.; Belfon, R.; Bernard, M. (2016), AgriMaps: Improving site-specific land management through mobile maps. Comput. Electron. Agric. 123, 292–296.
18. Kabbiri, R.; Dora, M.; Kumar, V.; Elepu, G.; Gellynck, X.(2018). Mobile phone adoption in agri-food sector: Are farmers in Sub-Saharan Africa connected? Technol. Forecast. Soc. Chang. 131, 253–261.
19. Kumar, A. (2019). Role of social media in the dissemination of agricultural innovations in Haryana (Doctoral dissertation, CCSHAU)
20. Kumar, M. (2019). Agriculture: status, challenges, policies and strategies for India. IJERT, 8, 12.

21. L. Zhao, Y. Lu, L. Zhang, and P. Y. K. Chau,(2012). Assessing the effects of service quality and justice on customer satisfaction and the continuance intention of mobile value-added services: an empirical test of a multidimensional model, Decision Support Systems, vol. 52, no. 3, pp. 645–656, 2012.
22. Martins, C., Oliveira, T., & Popovič, A. (2014). Understanding the internet banking adoption: A unified theory of acceptance and use of technology and perceived risk application. International Journal of Information Management, 34(1), 1–13.
23. Mendes, J.; Pinho, T.M.; Neves dos Santos, F.; Sousa, J.J.; Peres, E.; Boaventura-Cunha, J.; Cunha, M.; Morais, R.(2020). Smartphone Applications Targeting Precision Agriculture Practices—A Systematic Review. Agronomy, 10, 855.
24. Min, S.; So, K.K.F.; Jeong, M.(2018). Consumer adoption of the Uber mobile application: Insights from diffusion of innovation theory and technology acceptance model. J. Travel Tour. Mark.,36, 770–783
25. Minet, J.; Curnel, Y.; Gobin, A.; Goffart, J.-P.; Mélard, F.; Tychon, B.; Wellens, J.; Defourny, P.(2017). Crowdsourcing for agricultural applications: A review of uses and opportunities for a farmsourcing approach. Comput. Electron. Agric., 142, 126–138.
26. Mittal, S.; Mehar, M.(2012). How mobile phones contribute to growth of small farmers? evidence from India. Q. J. Int. Agric., 51, 227–244.
27. Molina-Maturano, J.; Verhulst, N.; Tur-Cardona, J.; Güereña, D.T.; GardeazábalMonsalve, A.; Govaerts, B.; Speelman, S.(2021). Understanding Smallholder Farmers' Intention to Adopt Agricultural Apps: The Role of Mastery Approach and Innovation Hubs in Mexico. Agronomy, 11, 194. https://doi.org/10.3390/ agronomy11020194
28. Oliveira, T.; Faria, M.; Thomas, M.A.; Popoviˇc, A.(2014).Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. Int. J. Inf. Manag., 34, 689–703.
29. Rajasekharan P ; Nair KM et al (2013). Soil Fertility Assessment and Information Management for Enhancing Crop Productivity. In: Rajasekharan P, Nair KM, Rajasree G, Sureshkumar P, Narayanankutty MC, editors. Agro-ecology of Kerala. Kerala State Planning Board; p. 54–71.
30. Rogers, E. (1962), Diffusion of Innovations, The Free Press, New York
31. Rogers, E.M. Diffusion of preventive innovations. Addict. Behav. 2002, 27, 989–993
32. Rose, D.C.; Sutherland, W.J.; Parker, C.; Lobley, M.; Winter, M.; Morris, C.; Twining, S.; Ffoulkes, C.; Amano, T.; Dicks, L.V. (2016). Decision support tools for agriculture: Towards effective design and delivery. Agric. Syst. 149, 165–174.
33. Sani, Lawal & B.Y., Boadi & Oladokun, Olugbade & Kalusopa, Trywell. (2014). The Generation and Dissemination of Agricultural Information to Farmers in Nigeria: A Review. IOSR Journal of Agriculture and Veterinary Science. 7. 102-111. 10.9790/2380-0721102111.
34. Singh, H., Kar, A.K. and Ilavarasan, P.V. (2017), Assessment of e-governance projects: an integrated framework and its validation", Proceedings of the Special Collection on eGovernment Innovations in India, ACM, pp. 124-133.
35. Szilagyi, R., & Herdon, M. (2006). Impact Factors For Mobile Internet Applications In The Agri-food Sectors. Advance online publication. https://doi.org/10.13031/2013.21882
36. Tech Trends 2016 Innovating in the digital era, Deloitte University press, 2016
37. Venkatesh; Morris; Davis; Davis (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Q., 27, 425.
38. Venkatesh; Thong; Xu (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. MIS Q. 36, 157
39. Williams, M.D.; Rana, N.P.; Dwivedi, Y.K.(2015). The unified theory of acceptance and use of technology (UTAUT): A literature review. J. Enterp. Inf. Manag., 28, 443–488
40. Tibbets, John H. (2018). "From identifying plant pests to picking fruit, AI is reinventing how farmers produce your food".; http://www.eco-business.com Retrieved 10 March 2022.
41. Agus, Sydney; Vanian, Jonathan (2017). "6 'Change the World' Companies That Are Rising Stars". http://www. fortune.com; Retrieved 10 March 2022.