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Farmer knowledge and the intention to use smartphone-based information management technologies in Uganda

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Abstract

Interest in using smartphone-based technologies for farm management is growing. However, existing research does not adequately address the effect of farmer knowledge and awareness in their intention to use such technologies. The aim of the present study is to identify the main factors that influence farmer intention to use a Farm Management Smartphone App (FMSA), with an emphasis on farmer knowledge. Ugandan dairy cattle farmers (n = 206) were interviewed before and after a training session that focused on the use of FMSA. The resulting data included farmer socio-demographics, data on their knowledge about the use of smartphones and related applications, and constructs of the Unified Theory of Acceptance and Use of Technology (UTAUT) extended with self-efficacy. Structural equation modeling (SEM) was used to examine the determinants of intention to use the FMSA. Farmer intention to use is mainly determined by self-efficacy, facilitating conditions and performance expectancy before exposure to the App. In contrast, the influence of effort expectancy and social influence only emerged after

completing the training. FMSA and similar technologies should therefore be as user-friendly as possible to sustain the farmers' intention to use an App. Promotional strategies should be designed to target specific characteristics of intended users.

Keywords: Awareness, Developing countries, ICT, Smartphone Apps, Technology acceptance

1 Introduction

Agri-food systems are increasingly characterized by the globalization of food markets and increased international trade (Munz et al., 2020). Changes in the food supply chain are also being shaped by consumer concerns about sustainability, environmental friendliness, quality and safety (Chen et al., 2021). Research addressing low agricultural productivity due to climate change has been growing in recent years (Hannus and Sauer, 2021; Kilelu et al., 2019). This combination of changes means that the agri-food system needs to transform to become more efficient, resilient and sustainable (Alexander et al., 2018), particularly in the Global South. Farmer use of information and communication technologies (ICT) appears to be an integral part of this transformation (Klerkx et al., 2019; Lajoie-O'Malley et al., 2020). Among others, ICT improves farmers' access to and use of relevant farm data, enhances record-keeping, monitoring and general farm management, and may lower agricultural production costs while increasing productivity (Barragan et al., 2016; Cisternas et al., 2020; Michels et al., 2019). Furthermore, some ICT tools such as mobile phones and smartphone-enabled information management applications (Apps) require minimal investment while offering a wide range of possibilities and benefits (Michels et al., 2020). In developed countries, the benefits of integrating smartphone-based information management technologies, such as smartphone Apps and information systems in farm management, are well-documented. For example, farmers can use the photography and audio-video capabilities of smartphones to access and interact with tailor-made, updated, reliable and farm-relevant information to improve their enterprises (Chipidza and Leidner, 2019; Kansiime et al., 2019; Teacher et al., 2013). Currently, the use of smartphone-based Apps should be promoted as an intensification strategy to increase food production without necessarily expanding agricultural area in sub-Saharan Africa (Brandt et al., 2020; Britt et al., 2018).

Despite the potential of mobile phones and smartphone-enabled Apps in the agriculture sector, little is known about their utilization by farmers (Bonke et al., 2018). Particularly in low-income countries (LICs), studies addressing their adoption and usage among farmers remain limited (Dwivedi et al., 2019; Landmann et al., 2021). This could be attributed to lack of awareness about the added value of smartphone-based technologies, which has caused them to remain new and under-utilized in LICs

(Michels et al., 2019; Taheri et al., 2020; Zhang et al., 2017). Some smartphone Apps have been utilized in smallholder farming systems for data collection (Daum et al., 2018) and detecting crop diseases (Mrisho et al., 2020). However, there are very few information management Apps, appropriate for such farming systems. Farmers are hardly aware of the few existing Apps that would meet their needs; it is the task of extension organizations to raise awareness about new or existing Apps (Schulz et al., 2021).

Previous studies (Jenkin et al., 2011; Mishra et al., 2014) show that these extension organizations are still in the early stages of raising awareness around such ICT tools. Four key types of barriers that potential users experience and impede adoption include knowledge gaps, practice gaps, opportunity gaps, and knowledge-doing gaps. Besides understanding the adoption barriers, some ICT acceptance studies have targeted determinants of intention to use in the sub-Saharan African context (Kabbiri et al., 2018; Muto and Yamano, 2009; Sekabira and Qaim, 2017). Nevertheless, the main focus of these studies has been on mobile phones in general rather than smartphone-based Apps. Furthermore, most of these studies employed the Technology Acceptance Model (TAM); hardly any have used the unified theory of acceptance and use of technology (UTAUT) approach. Kabbiri et al. (2018) suggest that more research is required concerning the acceptance of information management technologies in farming communities to understand how the characteristics of the intended user groups influence the use of such technologies. Such research could be conducted using the UTAUT model, as it is considered to be more helpful in developing smartphone App interfaces that are tailored to the needs of intended user groups (Landmann et al., 2021). In addition, this model can examine the relationship between socio-demographic characteristics of potential users (e.g., age, gender, and experience) and intention to use. This aspect is missing in most other models.

Research on adoption of smartphone-based agricultural information management technologies is mostly conducted in developed countries. Such research should be extended to LICs, which are characterized by a high concentration of smallholder farms (Michels et al., 2020; Schulz et al., 2021). The current study addresses this need by assessing the determinants of the intention to use smartphone-based information management Apps for farm management among Ugandan dairy farmers. In particular, we seek to i) evaluate how increased awareness and knowledge gained from targeted training affects farmers' perceptions, beliefs and attitudes towards a farm management smartphone App (FMSA), ii) determine whether behavioral determinants within the unified theory of acceptance and use of technology could explain the intention to use FMSA, iii) establish whether the intention to use FMSA changes after taking a training regarding the FMSA functionality, and iv) assess the effect of farm and farmer characteristics (i.e., production system, age, and experience) on the major factors that explain the observed intention to use FMSA. To the best of our knowledge, no similar study has been done in the context of a developing country in sub-Saharan Africa.

Section 2 describes the theoretical underpinnings of UTAUT. Section 3 presents the research methods used and the constructs aligning them to the proposed research model and hypotheses backed by previous literature. Results and discussion are presented in Section 4. Last, Section 5 presents a summary of the key findings and perspectives for future research.

2 Theoretical background

Technology acceptance and use are expected to be high when the potential adopters clearly perceive the anticipated benefits such as reducing time and production costs while executing daily farm activities (Abu-Khalaf and Hmidat, 2020; McDonald et al., 2016). The farmer's perception of the economic benefits of using smartphone-based technologies in agriculture may affect the degree of acceptance (Michels et al., 2019). For instance, it is very easy to demonstrate how the use of agricultural information management Apps can save time for farmers, but it is more difficult to quantify how such Apps can save them money. In addition, when the technology is targeted towards a farming enterprise that the farmer does not perceive to be a major source of income (Mills et al., 2017), it is unlikely that its acceptance and use will only be determined by the expected economic advantages. In such cases, behavioral factors may play a greater role. As the majority of dairy farmers in sub-Saharan Africa are small-scale subsistence farmers (Ahikiriza et al., 2021), they are likely to have another primary source of income. This makes it even more important to examine the influence of perceptions, beliefs and attitudes on farmers' intentions to use smartphone-based agricultural information management technologies.

To understand farmers' behavioral intention to use smartphone-based agricultural technologies, some studies have used TAM (Hannus and Sauer, 2021; Jimenez et al., 2021). Others have identified specific farmer user groups to model intention behavior based on UTAUT (Landmann et al., 2021). UTAUT explains 70% of the variance in intention behavior compared to the 30% explained by TAM (Chua et al., 2018; Venkatesh et al., 2003). UTAUT has been used in various contexts to study the behavioral factors that influence the use and acceptance of several mobile technologies (Akinnuwesi et al., 2016; Gunawan et al., 2019; Michels et al., 2019). For instance, UTAUT has previously been applied in various agricultural contexts, e.g., to examine the adoption of agricultural data collection technologies (Beza et al., 2018), soil and water conservation measures among farmers (Faridi et al., 2020), precision agriculture technologies (Li et al., 2020) and smart farming technologies (Ronaghi and Forouharfar, 2020). In the present study we chose to adapt and apply the UTAUT model because of its proven track record in predicting the intention to use new mobile technologies. However, UTAUT has hardly been used in studies on the adoption of agricultural information management Apps, particularly those designed for keeping farm records in the context of a developing country.

UTAUT is an integrated approach that consolidates variables from eight theories to explain information technology usage behavior (Venkatesh et al., 2003). These theories include: 1) the theory of reasoned action, 2) the technology acceptance model, 3) the motivational model, 4) the theory of planned behavior, 5) a combination of the technology acceptance model and the theory of planned behavior, 6) the model of PC utilization, 7) the innovation diffusion theory, and 8) social cognitive theory. UTAUT proposes four constructs to assess the behavioral intention and usage of technology, namely performance expectancy (PE), effort expectancy (EE), social influence (SI) and facilitating conditions (FC). Considering the key role self-efficacy (SEFF) plays in the use of new information management technologies (Rana and Dwivedi, 2015; Sezgin et al., 2017), the present study extended the UTAUT model with self-efficacy as a fifth construct derived from social cognitive theory. Self-efficacy regulates human behavior through cognitive, motivational, affective, and decisional processes (Benight and Bandura, 2004).

3 Materials and methods

3.1 Description of FMSA (Rwenzori dairy App)

We chose dairy FMSA as a case, inspired by the results of previous studies which showed that the use of herd/farm management smartphone Apps in developed countries can help to increase milk production (Borchers and Bewley, 2015; Michels et al., 2019). As milk provides most of the nutrients that malnourished people generally need, milk consumption is often promoted in developing countries (Britt et al., 2018). It is therefore not surprising that 70% of the population in Uganda consumes milk products at least once a week (Balikowa, 2011). However, this rate of intake is still not sufficient to meet the nutritional requirements of the hungry population in Uganda. Ideally, the per capita intake of milk in Uganda should grow at a rate of 2.7% per year (Waiswa et al., 2021). National milk production remains insufficient to satisfy the current demand, resulting in the need to import dairy products (Tadesse et al., 2018). To meet the current and future demand for dairy products, the Ugandan dairy sector will have to sustainably intensify milk production, by investing in more innovative farm management systems, e.g., farm management information systems (Hannus and Sauer, 2021; Munz et al., 2020) and herd information management Apps (Michels et al., 2019).

The Rwenzori dairy App is an FMSA designed to enhance record-keeping among dairy farmers in Uganda. The App was developed by the researchers in collaboration with dairy farmers and veterinary/animal husbandry officers. It was built based on the latest open-source Microsoft technology. Two servers are used to operate the App, the Blazor server for the farmers' section and ASP.NET Core for management of the App. The database (DB) used to store farmers' information is a Cosmos DB on Azure, a non-structured query language (non-SQL) database. Other user information (i.e., management) is stored on SQL Azure DB. Both databases (SQL and non-SQL) are hosted on the Azure cloud in South Africa. The FMSA can only be accessed through a commonly-used browser such as Chrome, Firefox, Edge and/or Safari, as it is not yet available on the Google Play store. The App operates on Android phones, PC and Mac in the following manner: once the information is entered, it goes to either of two servers. Depending on the user type, the information is later stored on Cosmos DB and SQL Azure DB for the farmer and management Apps, respectively (Fig. 1). More information on how to use/operate the App can be found in the user manual *(supplementary material)*.

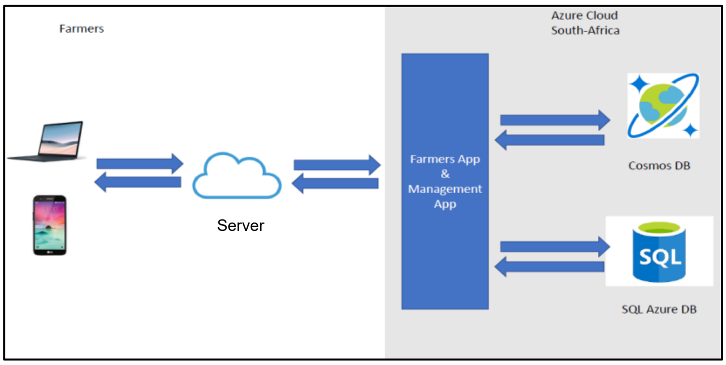

Fig. 1. Architectural design of Rwenzori dairy App (FMSA)

To begin using the App, only a login email and password are required. Dairy farm information (records) can be entered offline into the FMSA. The records saved on a smartphone, PC or Mac can be later uploaded to the server when internet access becomes available. The records captured in the FMSA fall into five main categories: farm staff, animal stock, tools and infrastructure, farm details, and production and productivity records (Fig. 2).

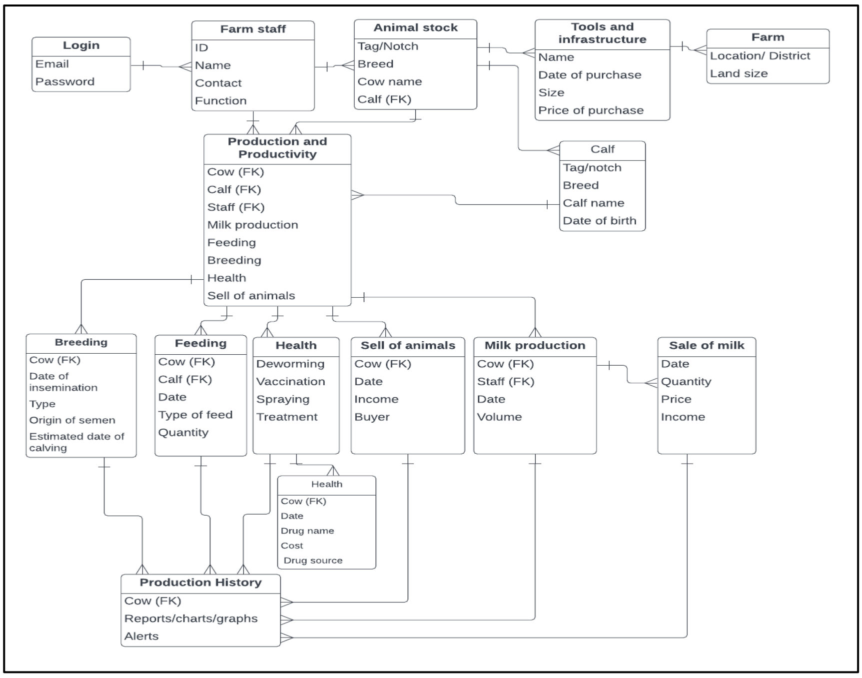

Fig. 2. Functional block diagram showing the major records captured by the App

To enter records related to production and productivity, the farmer must first enter information on farm staff and animal stock. All dairy farms require at least one dairy cow and at least one ‘staff member’ (in the form of either hired help or a family member). The foreign key, abbreviated as FK in the functional block diagram, simply means that particular records can only be entered if that FK item has already been entered in the system/App.

The App interface has three main sections: 1) Major dairy farming records (milk production, insemination/mating and calving dates, feeding of the cows, feeding of the calves in terms of the amount of milk fed to each calf and type of feeding used, sale of milk, sale of animals and animal health records); 2) tools, facilities/infrastructure, animal stock and farm staff (tools used in the day-to-day management of the farm, infrastructure such as dip tanks, a record of all animals on the farm and the details of the farm staff especially when the farm has permanent farm workers); and 3) settings. The App also has a help function. Fig. 3 presents the App interface that appears after entering animal stock and farm staff in the App (left), and the user interface showing how to add a new record for milk production (right). More details about the interfaces of the various major components of the App can be found in the *supplementary materials* or at https://cowanalytics.blob.core.windows.net/manual/RwenzoriDairyApp-UserManual.pdf.

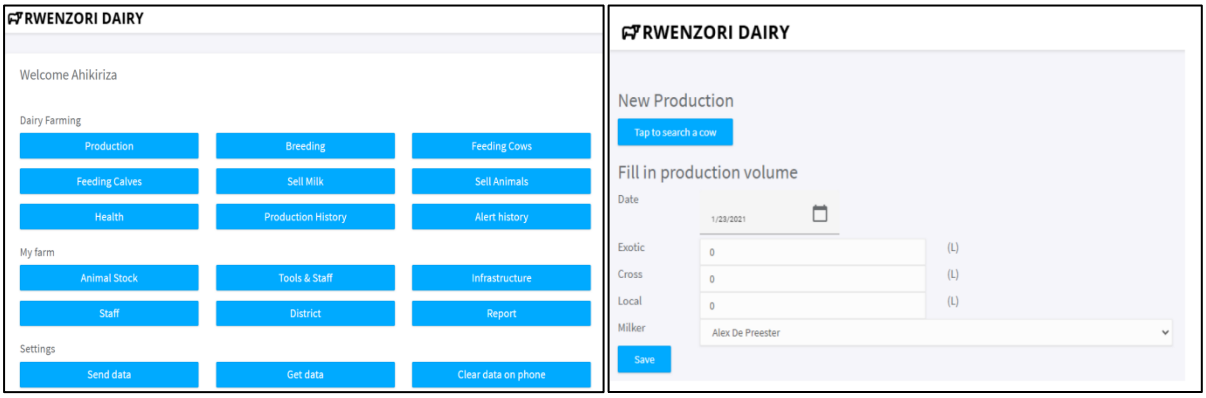

Fig. 3. User interfaces of the farm management smartphone-based App (FMSA)

3.2 Data collection

From a list of farmers provided by the district veterinary officers, 210 dairy cattle farmers were randomly selected from two districts of Uganda (Kabarole and Ibanda) and invited for a targeted training session. The aim of the training was to create awareness and teach the farmers how to use the Rwenzori dairy App. All of the selected dairy farmers owned at least 2 dairy cows, at least one of which was lactating at the time of the training. No other farmer characteristic was included in the selection criterion (not even ownership of a smartphone). Type of production system was also not chosen as part of the selection criteria for two reasons. First, in Uganda, the great majority (90%) of the dairy farmers and their herds belong to the small-scale subsistence production system (Balikowa, 2011). Second, no classification study had been conducted recently in the study area, resulting in a dearth of farmer lists specifying the type of production system. Although there was an unequal number of farmers invited from the various production systems, this accurately represents the dairy sector farmers in Uganda.

Farmers were invited in groups of 15 per day. The training was repeated during 14 days in March 2021, with a total of 206 participants completing the training. A structured questionnaire with two main sections was used to collect pre- and post-training data from each farmer on the day of their training. The first section included questions about the farmers' socio-demographic characteristics while the second contained questions on their knowledge about the use of smartphones and smartphone Apps and an evaluation of the constructs in the extended UTAUT. Selected items to measure theoretical constructs/latent variables (PE, EE, SI, FC and SEEF) were based on previous studies (Beza et al., 2018; Sezgin et al., 2017; Venkatesh et al., 2003; Venkatesh et al., 2012) to ensure content validity of the scales used. A seven-point Likert scale (1-7) ranging from "Entirely disagree" to "Entirely agree" was used for all the statements. Before the formal data collection, the questionnaires were pre-tested with a group of 15 dairy farmers to ensure that they were fit for the present study.

Prior to the start of each training session, one of the researchers and a team of three trained enumerators administered the questionnaire to the participants. After the farmers completed the interviews they attended a two-hour training session about the App. The training covered how to log in, the main sections of the App, the records to be entered, how to use the help function, the benefits of using the App, and how to generate periodic reports based on the records entered. The farmers were also allowed to suggest ways to improve the App to enhance its relevance and performance. After the training, the questionnaire was administered again (with only the questions related to the theoretical constructs) to evaluate whether the training had influenced the farmers' intention to use the App.

3.3 Research model and hypotheses

This section presents the hypotheses of theoretical determinants that explain farmers' intention to use smartphone-based information management technologies in dairy farming. These are formulated in the context of this study as elaborated below:

'Facilitating conditions' refers to farmers' beliefs regarding how the existing technical infrastructure and resources will help them to use the FMSA to capture farm records (Baabdullah et al., 2019; Venkatesh et al., 2012). Farmer knowledge and skills affect their decision to use the App, including knowledge about how to operate a smartphone, PC and/or Mac; how to log in to the App, and how to enter information, save it and send the data to the server. Moreover, ownership of a smartphone appropriate for installation of the dairy FMSA as well as access to sufficient mobile internet coverage can influence the farmers' decision to use the App (Michels et al., 2020). In summary, access to sufficient mobile internet coverage, possession of an appropriate smartphone, and access to knowledge related to the use of smartphone Apps all result in a stronger intention to use an FMSA. Therefore, we hypothesized that:

H1: Facilitating conditions (FC) have a positive effect on the intention to use FMSA.

'Effort expectancy' is the degree of ease associated with dairy farmers' use of the FMSA (Beza et al., 2018; Venkatesh et al., 2003). Dairy farmers differ in the frequency with which they are exposed to smartphones and related Apps. Those who are frequent users of smartphone-based technologies are likely to face fewer problems when using the FMSA for routine farm operations. Non-frequent users will have to evaluate the effort required to learn how to use such Apps before they choose whether to start using them (Tam et al., 2020). Non-frequent users are more likely to be attracted to user-friendly Apps that require less effort (Chua et al., 2018), thus the farmer's belief about the user-friendliness of an App will have a significant effect on acceptance. We therefore expect the farmer's belief about ease of learning and using the App to affect their intention to use it. We hypothesized that:

H2: Effort expectancy has a positive effect on the intention to use FMSA

‘Social influence’ is the extent to which dairy farmers perceive that significant others want to use the FMSA (Ronaghi and Forouharfar, 2020; Sahu and Gupta, 2007). Farmers are likely to consult their reference groups such as friends, colleagues and family about the use of new technologies. Farmers who desire social acceptance are likely to conform to the expectations of those in their social network, which may contribute to their behavioral intention to use new technologies. In addition, when farmers are part of a social network that places value on the use of such technologies, they are more likely to intend to use those technologies themselves (Schulz et al., 2021). We therefore hypothesized that:

H3: Social influence has a positive effect on the intention to use the FMSA

‘Performance expectancy’ is defined as the degree to which a dairy farmer believes that keeping dairy farm records using the FMSA will benefit him/her, either by improving the overall performance of the farm or making record-keeping easier and more efficient. This indicates that farmers will use the App if they believe that it will have positive outcomes in the day-to-day farm operations (Tam et al., 2020). It is therefore not surprising that several studies have linked performance expectancy to the adoption of smartphone-based Apps (Bonke et al., 2018; Chua et al., 2018; Michels et al., 2019). Similarly, other studies have consistently reported performance expectancy as the strongest determinant of intention to use information management technologies (Chong et al., 2012; Mehra et al., 2022; Venkatesh et al., 2003). Farmers may also evaluate the performance expectancy of such technologies like FMSA. The greater the benefits and value expected from such technologies, the stronger the intention to use them. FMSA offers potential benefits such as i) the ability to access farm records at any time, as smartphones can be used anywhere with network coverage, and ii) increased data safety in comparison with record books. Such benefits are likely to influence farmer use of the App. Therefore, as presented in Fig. 4, we hypothesized that:

H4: Performance expectancy has a positive effect on the intention to use FMSA

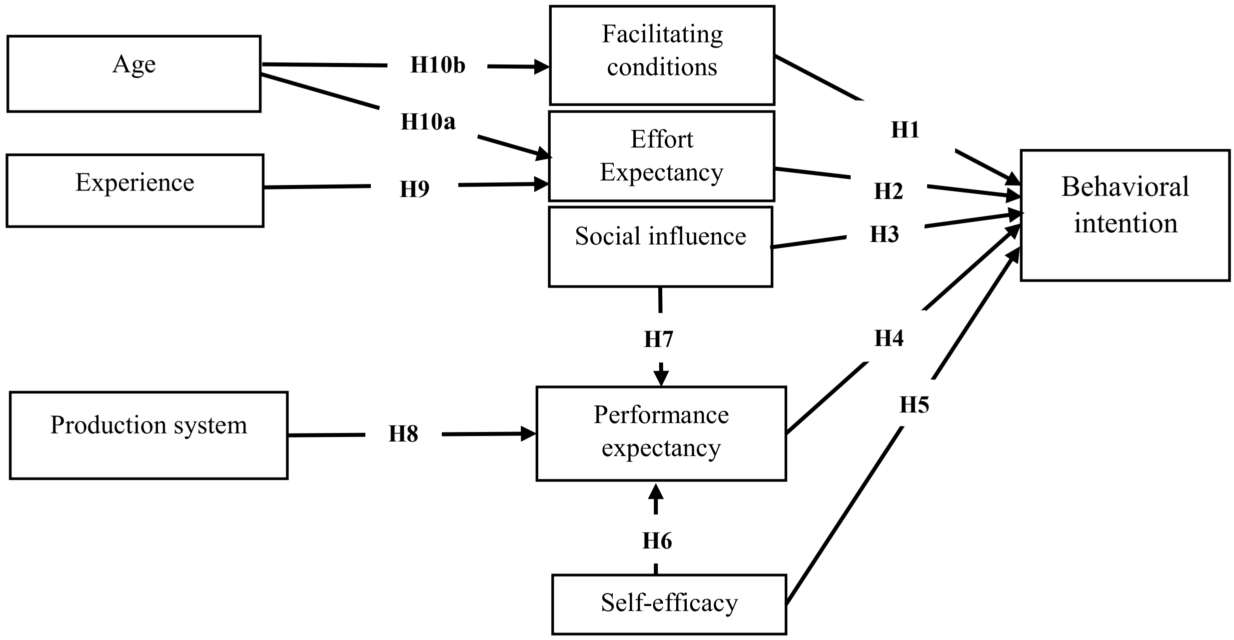

Fig. 4. Proposed research model (Extended unified theory of acceptance and use of technology (UTAUT) model based on Michels et al. (2019), Rana and Dwivedi (2015) and Venkatesh et al. (2003).

According to Mitchell et al. (1994), self-efficacy refers to "what a person believes he or she can do on a particular task". Alternatively, it can be defined as "an individual's belief in one's ability to organize and implement actions to carry out designated types of tasks," (Bandura, 1977). In our study, we refer to self-efficacy as the farmers' belief in their ability to use the FMSA. The effect of performance expectancy is also believed to be influenced by one's belief in his/her ability to use the FMSA (i.e., self-efficacy) and social influence (Rana and Dwivedi, 2015). Enhanced beliefs of farmers' ability to use FMSA could significantly influence their efficiency, productivity and performance when using the App. Additionally, if farmers believe that they can successfully use FMSA to produce the required outcome (i.e., to keep proper farm records), their intention to use the App will increase (Akinnuwesi et al., 2016). Based on existing literature, the proposed research model includes self-efficacy both as a direct predicting factor of intention to use smartphone agricultural information management Apps as well as a determinant for performance expectancy. In the same vein, because some people need to achieve membership in groups and obtain social support, these factors may influence their intention to use new technology (Ronaghi and Forouharfar, 2020). It is therefore likely that a dairy farmer will believe FMSA will be useful and provide added value when his or her fellow farmers, colleagues and/or friends consider using such an App to provide added value. Therefore, we hypothesized that:

H5: Self-efficacy (SEFF) has a positive effect on the intention to use the FMSA

H6: There is a positive relationship between self-efficacy and performance expectancy

H7: There is a positive relationship between social influence and performance expectancy

Michels et al. (2019) reported that achieving high milk yields and managing larger herd sizes have a positive effect on the perceived usefulness of herd management smartphone-based Apps. In our study, we consider the production system to be characterized by herd size, farm size, milk productivity per cow and level of commercialization (monthly milk sales) of the farmers as a determinant of performance expectancy. We therefore hypothesized that:

H8: Being in a highly productive production system (PS) of a more commercialized nature has a positive relationship with performance expectancy

We also considered the relationship between farmers' age and experience on effort expectancy and facilitating conditions, in accordance with previous studies (Michels et al., 2019; Venkatesh et al., 2003; Venkatesh et al., 2012). In our case, farmer experience was measured based on the number of years a farmer had used a smartphone. More experienced farmers were expected to have higher effort expectancy as compared to less experienced dairy farmers. Similarly, older dairy farmers were expected to have fewer facilitating conditions to enable them use the FMSA for farm record-keeping. We therefore hypothesized that:

H9: There is a positive relationship between experience (EXP) and effort expectancy

H10a: There is a negative relationship between farmer's age and effort expectancy

H10b: There is a negative relationship between farmer's age and facilitating conditions required to use the FMSA in farm record-keeping.

3.4 Statistical analyses

Data were analyzed using STATA (version 14). Descriptive statistics such as mean, standard deviation, frequencies and percentages were computed to profile dairy farmers and a paired sample t-test was performed to check for potentially significant differences. To do so, we evaluated whether there were significant differences in farmers' responses to the statements pre- and post-training. Structural equation modeling (SEM) was then used to test the formulated research hypotheses to understand whether predictors of intention to use the FMSA differed before and after the targeted training. SEM was considered the most appropriate technique for this study, not only because the study could benefit from existing theories but also because the technique allows simultaneous analysis of all relationships while combining multiple regression with factor analysis (Tabachnick et al., 2007). The study applied the maximum likelihood method to evaluate the measurement model. Reliability was assessed using Cronbach's alpha for each construct, while average variance extracted (AVE) and factor loadings obtained from confirmatory factor analysis (CFA) were used to determine convergent validity. Discriminant validity was then assessed by comparing the square root of AVE to the inter-construct correlations (Fornell and Larcker, 1981). The structural model was then evaluated in order to test the study hypotheses. Two models, based on the situation before and after training, were evaluated. By examining the differences between the two models we could thus determine the effect of increased awareness and knowledge (acquired through targeted training) on the intention to use FMSA. No single index was sufficient to assess the models (Park and del Pobil, 2013), thus several indices/measures were used to assess the suitability of both measurement and structural models: the ratio of Chi-square to degrees of freedom (χ^2/df), Chi-square (χ^2), Comparative Fit Index (CFI), Tucker Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR).

4 Results and discussion

4.1 Farmer characteristics

The majority of the sampled dairy farmers were male (78.6%) and only a few had attended post-secondary education. Of the farmers interviewed, 34.0% had completed primary school, 20.4% had completed secondary school and 6.8% had no formal education (Fig. 5). Although the majority of farmers had limited formal education and very few (14.1%) had a Bachelor's degree or a post-graduate degree, 93.2% had some formal education and were therefore literate.

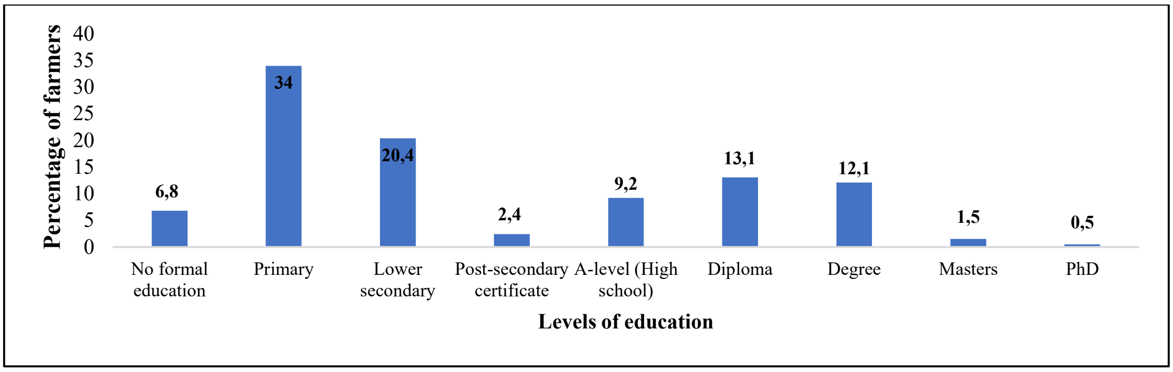

Fig. 5. Percentage of farmers and their levels of education

The majority (73.7%) of the farmers belonged to the small-scale subsistence dairy production system (Fig. 6). This is supported by the finding that the majority of the farmers (74.8%) owned fewer than 20 dairy cows and more than half (54.9%) sold a maximum of 20 liters of milk per day. This finding shows that despite some variance among farms in LICs, the majority of farmers from these countries operate at the subsistence level and such farmers may not view dairy farming as an important income-generating enterprise. Their decision to accept new technologies may therefore depend on several other factors besides the expected economic benefits (McDonald et al., 2016; Mills et al., 2017).

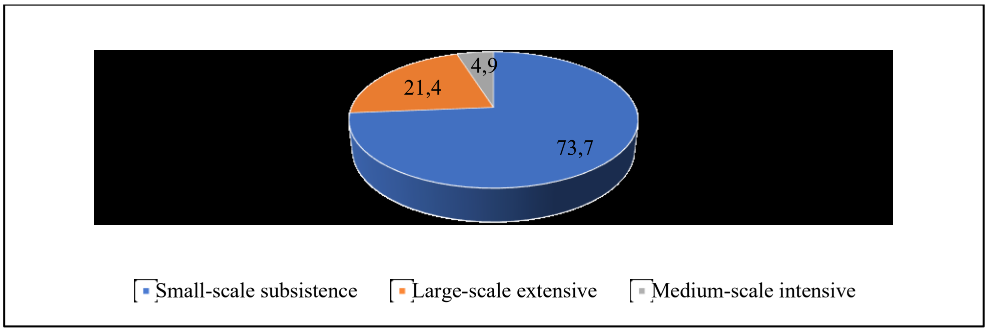

Fig. 6. Percentage of farmers in different dairy production systems

In total, 46.6% of the farmers owned smartphones and had used them for an average of 2.7 years. Among the total sample of dairy farmers, 53.9% had experience with internet related Apps but only a few (5.8%) were aware of other farming-related smartphone-based Apps (5.8%) (Fig. 7). This finding is supported by Zhang et al. (2017) who reported that such technologies are new and unfamiliar, especially among smallholders. Great efforts are therefore needed to raise awareness among smallholders, as they cannot possibly accept technologies that they are not even aware of.

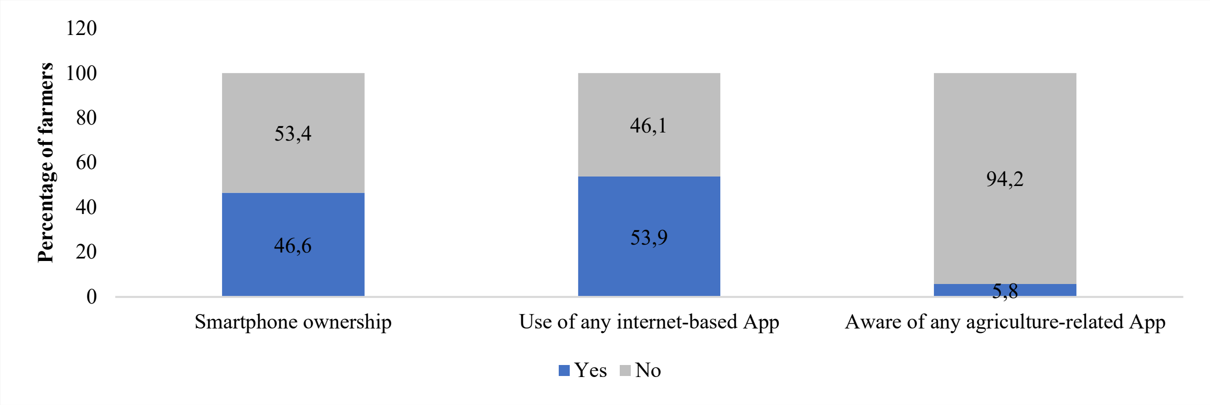

Fig. 7. Smartphone penetration and use of internet-based Apps among the dairy farming community

The mean age of the sampled dairy farmers was 47.7 years; more than half of them (50.5%) had less than a year of smartphone experience (Table 1). However, 61.7% stated that they had kept farm records for at least 11 years. This result shows that dairy farmers believed record-keeping to be an essential practice and others (25.7%) had also started doing it in recent years. Less than 1.0% of farmers had never kept farm records. Some farmers only recorded milk sales, however, and left out other important records such as breeding, animal health, milk production and feeding records. Possible explanations could be the farmers' perception of keeping records as a difficult task (Tham-Agyekum et al., 2010), while others could not realize the importance of keeping all these records.

Table 1: Socio-demographic characteristics of the sampled dairy farmers

Variable	Frequency	Percent (%)	Mean	Min	Max	SD
Age (Years)			47.67	24.00	86.00	14.50
21-30	28	13.59				
31-40	47	22.81				
41-50	44	21.36				
51-60	38	18.44				
61or older	49	23.79				
Experience in smartphone use (Years)			2.65	0.00	23.00	3.77
0	104	50.49				
1-5	62	30.10				
6-10	28	13.60				
11 and above	12	5.82				
Number of dairy cows owned			17.02	2.00	200.00	24.17

Variable	Frequency	Percent (%)	Mean	Min	Max	SD
2-19	154	74.75				
20-40	32	15.53				
41-60	12	5.82				
60 and above	8	3.88				
Milk produced day^{-1} in the dry season (L)			37.57	1.00	456.00	47.42
1-20	92	44.66				
21-40	54	26.21				
41-60	20	9.71				
61-80	20	9.71				
81 and above	20	9.71				
Milk sold day^{-1} (L)			30.76	0.00	450.00	43.24
0-20	113	54.85				
21-40	44	21.36				
41-60	24	11.65				
61-80	13	6.31				
81 and above	12	5.82				
Experience in record keeping (Years)			6.04	0.00	40.00	7.24
0	1	0.48				
1-5	53	25.73				
6-10	25	12.14				
11 and above	127	61.65				

Min= Minimum, Max= Maximum, SD= Standard deviation

4.2 Effect of targeted training on farmers' perceptions, beliefs and attitudes toward FMSA

On average, the level of agreement for all constructs was higher after the farmer training than before (Table 2). For instance, before training, the mean level of agreement for statements measuring performance expectancy ranged from 5.4 to 5.8 before training and increased from 6.0 to 6.6 after the training. The rise in agreement could be explained by an increased farmer awareness after the training about the functionality of the App including its advantages over the other traditional record-keeping methods (e.g., a record-keeping book and farm blackboard). This finding shows that knowledge can be increased through targeted training, which can in turn positively influence peoples' attitudes towards newly developed smartphone-based agricultural technologies (Putz et al., 2018). Furthermore, the result shows that technologies have a better chance of success when accompanied by significant awareness and trust building in the intended user community (Akinnuwesi et al., 2016; Schulz et al., 2021).

Similarly, the average perceived self-efficacy and effort expectancy increased after training from 4.4 to 5.1 and from 4.4 to 5.4, respectively. In other words, prior to the training, most farmers neither agreed nor disagreed with the statements measuring these constructs because they had insufficient knowledge about the App. For example, farmers did not know if it would be easy for them to learn the App, to use it, or whether they could develop a certain level of skill in using it. After being shown how it works, they had enough information to respond accurately. This result is consistent with Jeihooni and Rakhshani (2019) who found that educational interventions increase perceived self-efficacy, effort expectancy and perceived benefits among Iranian farmers. Pan et al. (2017) also reported that farmers are likely to change their behavior as they internalize information about a new technology, understand what they need to do, and why they need to do it. Therefore, citizen science and training can be used as complementary strategies to provide potential users with key information. While citizen science encourages the involvement of intended users and the use of traditional knowledge in design, training equips them with the technical knowledge needed to successfully capitalize on the use of new technologies (Paul et al., 2018).

After completing the training, 'performance expectancy' and 'intention to use the App' had the highest level of agreement (6.2), while 'facilitating conditions' had the lowest score (4.5). The marked increase in farmers' agreement with statements measuring the first two constructs suggests that farmers' perceptions of the technology are closely related to the knowledge they have about it. Knowledge refers to factual information and understanding of how the new technology works and what can be achieved by using it (Citroen, 2011). Increased knowledge boosts intention to use as the intended users always need relevant information to make such decisions (Esch et al., 2019). To increase the application of smartphone-based agricultural technologies, information on how to use such technologies and their expected outcomes should be prioritized in awareness building campaigns (Meijer et al., 2015). Furthermore, the small increase in 'facilitating conditions' after the training indicates that farmer knowledge about technology is not sufficient to accelerate their implementation of it. Knowledge should be supplemented with strategies that empower farmers to obtain the other resources, (i.e., financial, social and physical) required to facilitate the application of such technologies (Jarvis et al., 2020; Roberts et al., 2019).

The variation in the level of agreement regarding farmers' performance expectancy, perceived self-efficacy and behavioral intention decreased the most after training as revealed by the differences between the overall standard deviations of the constructs before and after training. This finding could be ascribed to a more homogeneous understanding of the advantages of using the FMSA among the farmers as a result of being exposed to the information shared during the training session. This result is in accordance with Ahikiriza et al. (2021) who reported that the utilization of relevant farm advice can reduce variation among farmers, as it facilitates movement from one production system to another. Additionally, the result reveals that targeted training can influence farmers' perceptions, beliefs and attitudes regarding their intention to use a particular technology (Pan et al., 2017).

Table 2: Mean of items, internal consistency and factor loadings per construct

Construct	Before training			After training			Mean difference	t-value
	Mean	SD	CFA loadings	Mean	SD	CFA loadings		
Performance expectancy (PE)	**5.55**	**1.45**		**6.23**	**1.05**		**0.68**	
PE1: Rwenzori dairy App will improve the way I manage my dairy farm records	5.78	1.58	0.887***	6.57	1.05	0.848***	0.791	-6.458***
PE2: Using the Rwenzori dairy App will enable me to do dairy farming as a business	5.50	1.37	0.901***	6.25	1.08	0.897****	0.743	-6.763***
PE3[a]: Rwenzori dairy App will make record keeping easier on my farm	5.58	1.58	0.845***	6.19	1.10	-	0.613	-4.824***
PE4: I think using the Rwenzori dairy App will enable me to keep accurate dairy farm records	5.42	1.33	0.798***	6.16	1.06	0.852***	0.738	-6.612***
PE5: Using the Rwenzori dairy App will enhance my overall effectiveness in dairy farm management	5.46	1.40	0.797***	5.99	0.97	0.784***	0.524	-4.613***
Effort expectancy (EE)	**4.38**	**1.71**		**5.44**	**1.47**		**1.06**	
EE1: I will find the Rwenzori dairy App easy to use	4.21	1.77	0.837***	5.39	1.62	0.881***	1.184	-10.222***
EE2: I believe that using the Rwenzori dairy App will be easy for me to learn	4.50	1.72	0.919***	5.60	1.49	0.943***	1.092	-10.451***
EE3: It will be easy for me to be skillful at using the Rwenzori dairy App	4.44	1.64	0.898***	5.33	1.30	0.892***	0.981	-9.953***
Social Influence (SI)	**4.71**	**1.46**		**5.19**	**1.44**		**0.48**	
SI1[a]: People who matter to me think that it makes sense to use the Rwenzori dairy App	4.35	1.56	0.850***	4.68	1.35	-	0.121	2.171**
SI2: People who influence my behavior think that I should use the Rwenzori dairy App	4.68	1.42	0.991***	5.21	1.50	0.868***	0.408	-3.253***
SI3: People who are important to me would use the Rwenzori dairy App themselves	5.11	1.41	0.736***	5.69	1.47	0.784***	0.617	-5.708***
Efficacy (SEFF)	**4.41**	**1.64**		**5.09**	**1.43**		**0.68**	

SEFF1: I think I would use the Rwenzori dairy App without help from anyone else	3.90	1.65	0.707***	4.46	1.44	0.739***	0.558	-4.024***
SEFF2: I think I would use the Rwenzori dairy App If there is someone to ask for help when I get stuck	4.56	1.58	0.935***	5.64	1.39	0.792***	0.374	-3.089***
SEFF3: I think I would use the Rwenzori dairy App if it has an in-built help facility for assistance	4.77	1.68	0.882***	5.35	1.45	0.733***	0.286	-2.218**
Facilitating conditions (FC)	**3.56**	**1.98**		**4.52**	**1.87**		**0.96**	
FC1: Rwenzori dairy App is compatible with the smartphone that I am currently using	3.52	2.28	0.961***	3.91	2.27	0.966***	0.379	-3.822***
FC2: I have reliable mobile internet coverage to use the Rwenzori dairy App	3.82	2.23	0.864***	4.27	2.13	0.855***	0.451	-4.302***
FC3[a]: I have the necessary knowledge to use the Rwenzori dairy App	2.90	1.73	0.746***	4.82	1.65	-	1.947	-13.466***
FC4: I can get help from others if I have difficulties using the Rwenzori dairy App	3.98	1.66	0.716***	5.09	1.42	0.635***	1.092	-7.804***
Behavioral intention (BI)	**5.37**	**1.87**		**6.20**	**1.47**		**0.83**	
BI1: I intend to use the Rwenzori dairy App in future	5.60	1.97	0.993***	6.39	1.50	0.981***	0.791	-6.388***
BI2: It is likely that I will use the Rwenzori dairy App on my farm	5.51	1.93	0.977***	6.35	1.47	0.989***	0.835	-6.770***
BI3: Rwenzori dairy App will be my favorite record-keeping method on my farm	5.00	1.73	0.833***	5.87	1.45	0.882***	0.869	-7.175***

Before training: Goodness of fit: Chi-square (174) = 337.17, $p<0.001$, $\chi^2/df= 1.938$, RMSEA = 0.067, CFI= 0.951, TLI=0.941, SRMR= 0.063

After training: Chi-square (120) = 260.433, $p>0.01$, $\chi^2/df= 2.170$, RMSEA= 0.075, CFI= 0.950, TLI=0.936, SRMR= 0.068

a = means the statement was removed to improve the model fit for the post-training model

Figures in bold represent the overall mean and SD of the different constructs

*** significant at $p<0.001$; **significant at $p<0.01$

4.3 Effect of targeted training on behavioral determinants of intention to use FMSA

Here we present results from the measurement and structural models before and after training the farmers. This highlights certain significant differences and the possible causes of those differences.

4.3.1 Measurement model (confirmatory factor analysis)

The model fit indices for the two measurement models were all acceptable except for the Chi-square test, which was significant ($p< 0.001$). For the pre-training model tested, both CFI and TLI were greater than 0.900; RMSEA was 0.067 (less than the limit of 0.080). The ratio of Chi-square to degrees of freedom was 1.938 (less than the limit of 3) and SRMR (0.063) was less than 0.090, as recommended by Hair et al. (2009) and Hu and Bentler (1999). To predict the post-training model, one statement from performance expectancy, social influence and facilitating conditions was removed to improve the model fit. This resulted in acceptable goodness of fit indices, i.e., the ratio of Chi-square to degrees of freedom was 2.170, CFI and TLI were 0.950 and 0.936, respectively, RMSEA was 0.074 and SRMR was 0.068.

The results also confirmed that all constructs had a Cronbach's alpha greater than 0.700 (Table 3) indicating acceptable construct reliability (Nunnally and Berstein, 1994). The results of the CFA model indicated that all items for each construct were statistically significant ($p<0.001$) and had acceptable factor loadings greater than 0.700. Furthermore, according to the method of Fornell and Larcker (1981), all constructs had AVE greater than the minimum acceptable value of 0.500, thus confirming convergent validity. By comparing the square root of the AVE in bold along the diagonal and the correlations between the constructs, the results showed that the lowest square root of the AVE was 0.747 and 0.755 for pre- and post-training, respectively. On the other hand, the highest correlations between constructs were 0.225 and 0.413, confirming discriminant validity. Therefore, the results of the evaluation of the measurement model confirmed an acceptable goodness of fit, sufficient discriminant validity and all constructs used in the study were suitable to test the path analysis of the structural model.

Table 3: Reliability and construct validity of the measurement model for before and after the training

	Construct							
Before training	PE	EE	SI	SEFF	FC	BI	CR	AVE
PE	**0.847**						0.926	0.717
EE	0.022	**0.885**					0.914	0.784
SI	0.002	0.025	**0.815**				0.824	0.664
SEFF	0.033	0.217	0.025	**0.797**			0.806	0.636
FC	0.003	0.101	0.020	0.095	**0.747**		0.820	0.558
BI	0.036	0.127	0.039	0.225	0.163	**0.938**	0.953	0.879
After training								
PE	**0.846**						0.717	0.715
EE	0.089	**0.906**					0.927	0.820
SI	0.087	0.041	**0.781**				0.734	0.611
SEFF	0.163	0.413	0.072	**0.755**			0.822	0.570
FC	0.001	0.059	0.016	0.054	**0.797**		0.702	0.636
BI	0.040	0.289	0.065	0.176	0.089	**0.934**	0.949	0.872

4.3.2 Structural model (Path analysis)

First, the model was tested for the pre-training situation. The model fit assessment confirmed acceptable values of indices, indicating a good fit. The ratio of Chi-square to degrees of freedom was 2.140, while the CFI and TLI were 0.920 and 0.909, respectively. RMSEA was 0.075 and SRMR was 0.077. The model explained 74% of the variance in the intention to use the FMSA for keeping farm records. The results revealed three significant determinants of intention to use the FMSA; Table 4 shows the supported hypotheses. Significant positive effects on intention to use were found for performance expectancy (β=0.135), facilitating conditions (β=0.298), and perceived self-efficacy (β=0.322). However, there was insufficient evidence to confirm the expected positive effects of effort expectancy (β=0.122) and social influence (β=0.098) on the intention to use FMSA prior to training.

Table 4: Results from path analysis used to test the proposed research model before and after training

Path	Before training			After training		
	Std.β	**p-value**	**Result**	**Std.β**	**p-value**	**Result**
FC → BI	0.298	0.000***	Supported	0.197	0.004***	Supported
EE → BI	0.122	0.100	Not supported	0.450	0.000***	Supported
SI → BI	0.098	0.132	Not supported	0.133	0.077*	Supported
PE → BI	0.135	0.037**	Supported	0.002	0.978	Not supported
SEFF→ BI	0.322	0.000***	Supported	0.106	0.237	Not supported
Predictors of performance expectancy, effort expectancy and facilitating conditions						
SEFF → PE	0.175	0.019**	Supported	0.363	0.000***	Supported
SI → PE	0.013	0.857	Not supported	0.226	0.005***	Supported
PS→ PE	-0.089	0.206	Not supported	0.06	0.935	Not supported
EXP → EE	0.256	0.000***	Supported	0.249	0.000***	Supported
Age → EE	-0.324	0.000***	Supported	-0.292	0.000***	Supported
Age → FC	-0.294	0.000***	Supported	-0.232	0.001***	Supported

Model fit before the training: Chi-square (240) = 514.53, p<0.001, Chi-square/df= 2.140, RMSEA = 0.075, CFI= 0.920, TLI=0.909, SRMR= 0.077; after training: Chi-square (177) = 461.871, p<0.001, Chi-square/df= 2.610, RMSEA = 0.076, CFI= 0.951, TLI=0.901, SRMR= 0.078; *** significant at p<0.01, **p<0.05, *p<0.1

Second, the model was tested for the situation after targeted training. Its goodness of fit indices were also acceptable, resulting in an appropriate representation of the data (Chi-square/df, 2.610; CFI, 0.951; TLI, 0.901; RMSEA, 0.076; SRMR, 0.078). The model explained 71% of the variance in the intention to use the App, generating results similar to the original model from Venkatesh et al. (2003). After training, the key determinants of intention to use were social influence (β=0.133), facilitating conditions (β=0.197) and effort expectancy (β=0.450). This finding indicated that the proposed research model yielded different results for the pre- and post-training situations. These results confirmed that increased awareness and knowledge gained through targeted training could explain differences in the determinants of intention to use new smartphone Apps for information management in agriculture, as suggested by Ahmed et al. (2016). The result also suggests that two distinct categories of target users (i.e., those with limited awareness and those with enhanced awareness) might exist. These may differ not only in perceptions, beliefs and attitudes but also in the factors that influence their intention to use information management Apps. Targeted promotional strategies are needed to address the needs of both groups.

Before training, perceived self-efficacy was the major determinant of intention to use the FMSA. A mere one-unit increase in perceived self-efficacy increased farmer intention to use the FMSA by 32.2%, a finding that is supported by the studies of Holden and Rada (2011) and Zhang et al. (2017). Further improving self-efficacy (e.g., through training) is therefore key to encourage the use and acceptance of farming-related Apps among farming communities in developing countries like Uganda.

Effort expectancy was not a significant determinant of intention to use the App prior to the training, but it became the most important determinant after training ($\beta=0.450$, $p<0.01$). After the training, a one-unit increase in the level of ease associated with the use of the FMSA by dairy farmers increased intention to use FMSA by 45.0%. Although our pre-training results ($\beta=0.122$, $p=0.100$) contrasted with several other studies which reported that effort expectancy is a significant determinant of intention to use new technologies (Chao, 2019; Dwivedi et al., 2019; Ronaghi and Forouharfar, 2020), our post-training results did confirm results from these other studies. Such inconsistencies could be attributed to differences in farmers' knowledge before and after the training in terms of how much effort was required to learn how to use the App. This is supported by Abubakar and Ahmad (2013) who found that awareness of the existence, features, cost, benefits and simplicity of new technologies moderates effort expectancy regarding intention to use.

Chua et al. (2018) reported that the complexity of the technology lowers potential users' intention to use it and Michels et al. (2019) recommend a simple and user-friendly interface for herd management Apps. Smartphone hardware as well as software may have a significant impact on intention to use for frequent smartphone users (Hsiao, 2013). Our findings regarding ease of use also support the idea that if potential users find it effortless to interact with the smartphone hardware on which the App is installed, their intention to use the FMSA may become greater than usual (Palos-Sanchez et al., 2021). This is because the usability of a smartphone usually precedes the use of the App itself. Improved hardware infrastructures such as faster processors and highly stable 4G networks should be made available in order to increase the intention to use FMSA among people who are already aware of such technology.

Our results also showed that social influence ($\beta=0.133$, $p<0.1$) significantly determined the intention to use the newly developed FMSA after training. In other words, if farmers become more aware of the FMSA and they associate with peers who have a positive attitude towards using the FMSA, these conditions will reinforce their intention to use FMSA. This contrasts with studies (Beza et al., 2018; Merhi et al., 2019) that report a non-significant association between social influence and intention to use new technologies. Even before training, the result was different from the post-training result. This indicates that even if perceptions, beliefs and attitudes of peer/social groups influence farmer intention to use FMSA, the influence of third-party expectations on intention to use FMSA plays a more crucial role in the decision-making process of potential users that have enhanced awareness of FMSA than those with limited awareness. In addition to mass promotional campaigns through radio programs and training for farmers, peer-to-peer extension approaches could also play a significant role in increasing the acceptance and use of information management technologies (Schulz et al., 2021). Consequently, peer-to-peer extension approaches and mass awareness raising campaigns should be viewed as complementary strategies rather than alternatives. However, our pre- and post-training results indicate that mass awareness raising campaigns should be preceded by peer-to-peer extension approaches to achieve the best results.

Surprisingly, pre-training performance expectancy had a significant impact on intention to use FMSA ($\beta=0.135$, $p=0.037$) but this dropped to non-significant levels after training ($\beta=0.002$, $p=0.978$). Before attending the training, a one-unit increase in the degree to which dairy farmers believed that keeping records using the FMSA would benefit them increased their intention to use the App by 13.5%. This is in accordance with the results of Gunawan et al. (2019) and Li et al. (2020) that indicate a positive influence of performance expectancy on intention to use. After training, the non-significant relationship was unexpected as it is believed that increased awareness of the benefits of the App would encourage even those without a smartphone to buy it, install the App and ultimately use it, but our study results indicated the opposite. Our results can be attributed to a reduction in variation in farmers' perceptions of the benefits of FMSA after the training. By presenting information that highlighted the benefits of the App, the knowledge gap among the farmers was greatly reduced. This explanation is supported by the findings of McDonald et al. (2016) who report that when the benefits of using a particular technology become apparent to the majority of target users, such benefits can no longer affect intention to use that technology.

Interestingly, 'facilitating conditions' was the only factor that significantly affected behavioral intention both before and after training. Access to sufficient mobile internet coverage, an appropriate smartphone and knowledge concerning the use of mobile smartphone Apps are universal determinants of intention to use among all intended users of new smartphone-based information management technologies. This is in accordance with Zhang et al. (2019) who emphasized the significance of better facilitating conditions in order to increase the use of smartphone-based Apps. This highlights the need for programs that enhance farmers' social, physical and financial assets, which will lead to increased acceptance and utilization of such technologies in farm management (Jarvis et al., 2020; Roberts et al., 2019). To further improve the use of information management Apps, training during awareness campaigns should not only focus on showing the benefits and improving farmers' skills but also on how to improve access to specific services such as affordable internet access for mobile devices.

4.4 Effect of farm and farmer characteristics on key determinants of intention to use FMSA

Within the present study we explored the influence of farm and farmer characteristics on facilitating conditions, effort expectancy and performance expectancy. The results revealed that the farmers' self-efficacy positively and significantly affected their performance expectancy both before and after the training. This means that farmers who thought they could use the FMSA observed more benefits of using the App than those who did not think they could use it. Consistent with this finding, Schwoerer et al. (2005) reported that self-efficacy is both a target of training as well as a desirable outcome as it improves the performance of new technologies. Therefore, trainings that increase self-efficacy should be effective in meeting the goal of improving perceived performance expectancy.

Before training, age had a significant but negative relationship with facilitating conditions (β= -0.294) and effort expectancy (β= -0.324). On the other hand, experience had a positive relationship with effort expectancy (0.256). These relationships remained the same even after the training. Such results indicate that older farmers have fewer facilitating conditions than younger ones. Similarly, an increase in age was associated with a lower perceived ease of learning how to use the App. The more years of experience a farmer had with using a smartphone, the less difficulty they perceived in using the App regardless of prior level of awareness about the App.

After training, social influence had a positive relationship with performance expectancy. This reveals that the farmers with a greater need to learn from either their peers or socially influential people are likely to perceive the new technology as more useful after increasing their awareness. This result, which is in accordance with Rana and Dwivedi (2015), can support communication with policymakers, namely that training sessions and peer-to-peer extension approaches should be seen as complementary methods of delivering advisory services. This combination can lead to networking systems that integrate knowledge production, adaptation and advice in order to promote technology transfer (Kilelu et al., 2019; Sutherland and Marchand, 2021).

Prior to training, the farmers that belonged to a more commercialized and more productive production system had a positive but non-significant relationship with performance expectancy. However, this changed to a negative relationship after completing the training. This unexpected negative shift could be ascribed to the increased information about the advantages of using FMSA by majority of the small-scale subsistence farmers after the training. Alternatively, this result could be because farmers who belonged to a highly productive commercialized production system did not find the FMSA as useful as they perceived it to be before the training session. Knowledge sharing between the designers and the users can improve the technology to best fit the needs of the target users (Beza et al., 2018). This may consequently reduce future dis-adoption levels of new technologies.

5 Conclusions and perspectives for further study

From our results, we conclude that the extended UTAUT model used in the study provides a solid foundation for understanding the determinants of intention to use new information management technologies in LICs. The two models explain more than 70% of the variance in intention to use the proposed farm management smartphone App. Second, our study shows that knowledge not only influences farmers' perceptions, beliefs and attitudes towards the use of new smartphone-based information management technologies in agriculture, but also the most important determinants of intention to use such technologies. The differences in the determinants of intention to use FMSA before and after training indicate that when introducing an information management technology in a farming community, awareness campaigns should focus on improving farmers' self-efficacy, facilitating conditions and performance expectancy. However, as farmers become more familiar with such technologies, effort expectancy and social influence can also be considered to encourage farmers to remain interested in using these technologies. Therefore, as important as it is to create awareness by highlighting the benefits of new information management technologies and enhancing farmers' self-efficacy, it is equally necessary to keep the design of such technologies simple and user-friendly in order to increase their usage among the intended user communities. In general, ensuring that mobile internet and proper smartphones remain affordable for farmers would greatly increase farmers' intentions to use such technologies.

This study examined the effect of knowledge on intention to use a new agricultural information management technology. We also recommend further research to examine the effect of knowledge on technology dis-adoption. Understanding the determinants of dis-adoption of smartphone-based information management Apps in agriculture can sustainably increase their use over time. In addition, some practical deployment issues pointed out by Wan et al. (2020), such as the impact of training costs, risks related to security and leakage of private information entered into the App and actual financial returns from using the App were not examined in this study. Gathering such data and integrating them with behavioral factors in a model to examine the intention to use smartphone-based information management Apps would yield insights that could increase the successful adoption of technological innovations in agriculture.

Targeted training such as the training studied here has been shown to increase awareness and knowledge, which in turn positively influence beliefs, perceptions and attitudes towards new information management technologies. However, training alone may not be enough to sustain the use of these technologies over time. The impact of social influence on intention to use indicates the usefulness of peer-to-peer extension approaches as a complement to training, especially among the intended users whose awareness has already been heightened. Peer-to-peer extension approaches could fail if the most appropriate peers are not correctly identified and recruited. Future research should focus on addressing this issue in order to maximize the benefits of peer-to-peer learning.

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