Intention to participate in smartphone-based data collection: The case of smallholder farmers in Uganda

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Abstract

Smartphone technology is increasingly being used to conduct surveys, including in low-income countries where the timely collection of socio-economic data is of great importance. This study investigated the intention of Ugandan smallholder farmers to participate in smartphone-based data collection (SPDC). The data was collected through a cross-sectional survey of 306 smallholder farmers. The results show that the willingness of farmers to participate in SPDC is high. The intention to participate in SPDC is directly influenced by attitude, subjective norms and perceived enjoyment. Indirect influences are perceived usefulness, perceived trustworthiness and perceived cost through their effects on attitude. Similarly, perceived ease of use indirectly influences intention through its effects on perceived usefulness and perceived enjoyment. Statistically significant differences were found in terms of age, gender, mobile phone ownership and education. These results show the great potential of SPDC for data collection in Uganda for researchers, policy makers, agribusinesses and stakeholders.

Keywords: Intention; smallholder farmers; smartphone-based data collection; survey; extended technology acceptance model, Uganda

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1. Introduction

Although the potential of mobile services as a means of providing development opportunities for smallholder farmers has been widely recognised and explored (Baro & Endouware, 2013; Duncombe, 2011; Gollakota et al., 2020; Jain et al., 2014; Mugwisi et al., 2014; Namyenya et al., 2021; Wyche & Steinfield, 2015), less attention has been paid to the potential of using smartphones as data collection tools to gain information on smallholder farming systems (Daum et al., 2018). It is crucial that scientists researching smallholder farming systems obtain high quality data, as ‘ data’ is considered one of the most valuable resources of our time (Qureshi, 2020). In many low-income countries (LICs), i.e. countries with a gross national income (GNI) per capita of USD 1,145 or less in 2023 (World Bank, 2024), planning, budgeting and policy-making in the agricultural sector is hampered by glaring gaps in the availability of agricultural and rural data (Kalibata & Mohamedou, 2021). Consequently, this lack of quality data poses a challenge when it comes to information asymmetry, climate shocks, poor market linkages and food scarcity (Carletto et al., 2015; Giroux et al., 2019). Furthermore, this lack of data directly hampers the ambitions of many LICs in terms of economic growth and poverty reduction (Kalibata & Mohamedou, 2021).

Normally, data on smallholder farming systems in sub-Saharan Africa are collected for socio-economic studies through extensive household surveys based on paper and pencil (Daum et al., 2018). This makes data collection tedious, error-prone and time-consuming (Tomlinson et al., 2009). Methods and tools need to be developed that utilise technological advances for more efficient data collection in order to quickly and accurately obtain relevant and up-to-date information on smallholder food production systems (Carletto et al., 2015). Advances in information and communication technology (ICT) could be the answer to this need as they enable the easy integration of data collection and input processes (Shirima et al., 2007). In particular, the advancement and widespread use of smartphone technologies provide social scientists and researchers with cost-effective and viable options for data collection (Keusch et

[1] The classification of countries according to the World Bank designations divides countries into four categories, i.e. low-income, lower-middle income, upper-middle income and high-income, based on gross national income (GNI) per capita in the past year. Countries with a gross national income (GNI) per capita of USD 1,145 or less in 2023 are categorised as low-income, while countries with a GNI per capita of more than USD 14,005 in 2023 are categorised as high-income according to the World Bank (2024). With a GNI per capita of USD 980, Uganda therefore falls into the group of low-income countries. The terms "low-income countries" and "high-income countries" as used in our manuscript do not necessarily reflect our view or assessment of the level of development or stages in the development process of a particular country.

al., 2019), and open up new opportunities to engage with resource-limited populations that were previously inaccessible (Somani et al., 2009). This is particularly important in sub-Saharan Africa, where there is an increasing need for comprehensive agricultural surveys despite limited research infrastructure (Bell et al., 2016).

Smartphones offer a variety of tools for data collection (Wenz et al., 2019), e.g. computer-assisted telephone interviews (CATI) (Lavrakas et al., 2017), and Short Messaging Services (SMS) for short questions (Conrad et al., 2017). Researchers can also conduct mobile surveys via browsers or applications (Couper et al., 2017) and use smartphones to passively collect data without actively involving the observed individuals or requiring explicit input from them (Keusch et al., 2019). This passive data collection includes the use of sensors to automatically record environmental parameters and wearable fitness trackers that monitor physical activity and health metrics (Pinter, 2015; Revilla et al., 2019; Sagvari et al., 2021).

As data collection tools, smartphones complement and help to address some of the disadvantages of paper-based surveys, including the risk of data loss, increased transcription errors, low data quality, longer data collection time and low efficiency of data collection in the field (Falzon et al., 2021; Ochoa Gómez, 2022). In addition, data collection via smartphone increases compliance with complicated or contextualised questionnaires, as it can facilitate the selection of questions to be answered or skipped (Somani et al., 2009).

Outside of the agricultural context, mobile devices, particularly smartphones, are the most commonly used tools for general data collection and transmission (Robert et al., 2015). This is partly due to the unprecedented proliferation of mobile phones around the world, making them one of the most ubiquitous technology. In sub-Saharan Africa, 515 million people, or 46% of the population, had subscribed to mobile phone services at the end of 2021, and it is predicted that another hundred million subscribers will be added by 2025, bringing the total number of subscribers to 613 million (50% of the region's population). Smartphone penetration in sub-Saharan Africa is expected to reach 88% by 2030 (GSMA, 2023). In Uganda, active mobile subscribers (30.55 million) accounted for 63.8% of the total population at the beginning of 2023 (UCC, 2023). The fact that a growing number of people own mobile phones is encouraging and could have a significant impact on the advancement of agricultural research (data collection). According to Somani et al. (2009), mobile phones hold significant potential to improve the effectiveness and efficiency of data collection in LICs.

However, the phenomenon of mobile research in LICs remains largely unexplored, and there is little literature on the use of SPT as a means of data collection in LICs (Robert et al., 2015). Nevertheless, there have been limited smartphone-based data collection (SPDC) initiatives in various countries (e.g., Bell et al., 2016; Daum et al., 2018; Ouma et al., 2019; Quinn et al., 2011). These earlier studies addressed methodological issues and criteria related to the relationship between SPDC and traditional methods. For example, the usability and feasibility of SPDC was investigated (El Ayadi et al., 2020; Heinonen et al., 2012; Thumbi et al., 2019; Wamwenje et al., 2019). While Bell et al. (2019) looked at recall bias and measurement error, Keusch et al. (2020) examined coverage errors associated with mobile phone-based surveys in combination with passive measurements. Other researchers evaluated the role of personalised feedback on participation and reporting (Wenz et al., 2020) while others examined response rates in the context of mobile surveys (Anhoj & Moldrup, 2004).

The results of smartphone-based studies with the general population in high-income countries (HICs) show that participation in this type of data collection is low (Jäckle et al., 2019; Keusch et al., 2022; Struminskaya et al., 2021). The full potential of SPDC could be limited by the willingness of the target population to participate (Wenz, 2019; Wenz & Keusch, 2023). Amany and Krishna (2017) have shown that the response rate of surveys is significantly influenced by the interests and intentions of the study participants. Empirical research, particularly on the willingness and intentions of smallholder farmers to engage in SPDC, is lacking. This knowledge gap could pose a major challenge in applying this approach to collect agricultural information/data from smallholder farmers in resource-constrained contexts such as Uganda. Should farmers who choose not to participate in SPDC show differences in important study factors compared to participants, the resulting non-participation could bias the results (Wenz & Keusch, 2023).

This study presents the results of a cross-sectional survey of Ugandan smallholder farmers conducted to assess the determinants of their intention to participate in SPDC.

*1.1. **A unified theoretical framework***

When researching the acceptance and use of information and communication technologies, intention-based models provide valuable insights into a person's behavioural intentions to predict their technology acceptance and use (Bothma & Mostert, 2023; Lee et al., 2021). In the area of technology acceptance overall, and in particular when examining people's willingness to use smartphones as a means to collect data or participate in surveys, previous research in non-agricultural settings, particularly in HICs, has relied on a variety of behavioral models (Beierle et al., 2019; Bosnjak et al., 2009; Di Matteo et al., 2018; Galesic & Bosnjak, 2009; Keusch, 2015; Keusch et al., 2019; Mate et al., 2023; Ochoa & Revilla, 2023; Ochoa Gómez, 2022; Wenz et al., 2017). Among the frameworks to explain technology acceptance and use are the Theory of Planned Behaviour by Ajzen (1991), the Theory of Reasoned Action (TRA) by Ajzen and Fishbein (1975) and the Technology Acceptance Model (TAM) by Davis (1989).

The TRA states that a person's intention to engage in a behaviour is mainly influenced by their attitude towards the behaviour and the subjective norms that represent the perceived social pressure associated with performing or not performing the behaviour (Aziz et al., 2020; Sok et al., 2020). This theory provides a basis for understanding the cognitive processes that lead to behavioural intentions (Ajzen & Fishbein, 1975). TPB extends TRA by incorporating perceived behavioural control and emphasizes the importance of internal and external factors in shaping intentions (Ajzen, 1991). Both TPB and TRA highlight the importance of attitudes and subjective norms in the formation of behavioural intentions. On the other hand, TAM, as an adaptation of TRA (Naseri et al., 2023) specifically tailored to modelling user acceptance of information technology, builds on TRA by introducing perceived usefulness (PU) and perceived ease of use (PEOU) as critical determinants of user attitudes and behavioural intention to adopt a new technology (Davis, 1989; Kalayou et al., 2020). The practical value of the TAM model lies in its emphasis on PU and PEOU, two elements that technology system designers can directly influence (Bosnjak et al., 2009). TAM assumes that PEOU and PU influence the individual attitude and intention to use a new technology (Davis, 1989; Koloseni et al., 2021). According to this theory, the easier a technology is to use and the more useful it is perceived to be, the more favourable are people's attitudes and intentions to use it. PU is a person's subjective expectation that using a new technology will improve their performance on a particular task (Davis, 1989). The extent to which smallholder farmers believe that the use of smartphones would enable their effective and efficient participation in survey research, e.g. by saving time, was operationalized as PU in this study. Smallholders' expectation of the potential effort required to participate in the SPDC is labelled as PEOU.

There are different views on which model is best suited to understand individual acceptance and use, especially in the field of ICT (Bothma & Mostert, 2023). The TAM, for example, has encountered some criticism when it comes to explaining user behaviour (Chandio et al., 2017; Hai & Alam Kazmi, 2015; Lim et al., 2016). Some scholars have argued that the primary constructs of the TAM (i.e., PEOU and PU) do not accurately or adequately capture the influences of context of use and technological aspects that might alter a user's adoption behaviour (Chuttur, 2009; Luarn & Lin, 2005; Malhotra & Galletta, 1991), while others view the TAM as either overly simplistic or outdated (Alshammari, 2024; King & He, 2006; Ramdhani, 2009; Shachak et al., 2019).

Despite these criticisms, TAM remains a widely recognised and popular framework among scholars in the field of information communication systems and technology use (Kelly & Palaniappan, 2023; Rad et al., 2022; Singh & Srivastava, 2020; Zhang et al., 2018). This recognition underpins the position of the TAM as a comprehensive and extensively researched model for understanding user acceptance of technologies in different domains (Jushermi et al., 2024; Praveena & Thomas, 2014). A growing body of empirical data supports the effectiveness and validity of the TAM in predicting and explaining individual intentions and technology use (Bosnjak et al., 2009; Ronald Kabbiri et al., 2018; Wenz & Keusch, 2023). Al-Emran and Granić (2021) confirmed in their research that the TAM and its extensions are still relevant and applicable in different domains and contexts. The TAM is recognised as a robust and accurate model for predicting user behaviour in a variety of information technology systems (Diaz et al., 2021; Venkatesh & Davis, 2000).

The evolution of technology and the diversity of user experiences necessitate constant refinement and adaptation of theoretical models (Ajibade, 2018). Therefore, previous studies have suggested introducing additional factors to the TAM model to improve its adaptability, explanatory power and specificity (Maillet et al., 2015; Taherdoost, 2017; Wixom & Todd, 2005). It is also emphasized that the inclusion of external as well as intrinsic motivation variables is crucial when researching technology acceptance (Davis, 1989; Wahab & Shariffadeen, 2019), and that it leads to more reliable predictions of technology use and acceptance (Taherdoost, 2017). Studies on mobile technology adoption using TAM have considered these propositions and examined the influence of additional variables on adoption and behavioural intentions. For example, Ronald Kabbiri et al. (2018) have extended the TAM to include perceived advantage and socioeconomic characteristics, while other scholars have introduced variables such as cognitive absorption, perceived credibility, perceived self-efficacy, perceived compatibility, and product involvement (Sorce & Issa, 2021; Tiwari & Tiwari, 2020; Zainab et al., 2017). Therefore, in line with previous studies, and a thorough review of the literature (Al-Mamary et al., 2016; Bosnjak et al., 2009; Ronald Kabbiri et al., 2018; Naseri et al., 2023; Wenz & Keusch, 2023), this study extends the TAM by examining perceived trustworthiness, perceived cost, perceived enjoyment and subjective norms, in addition to the core TAM variables. In doing so, we aim to increase the predictive validity of the TAM and also provide a deeper understanding of the smallholders' intention to participate in SPDC. The socio-cultural and economic environment in which farmers operate can influence technology adoption in ways that were neither expected in previous studies (e.g. Bosnjak et al., 2009) nor consistent with global trends (Ajibade, 2018). Therefore, the application of the TAM can and should be tailored to the unique characteristics of each study population and technological context. By applying the TAM extension in this study, we contribute to theoretical insights on whether the temporal and contextual factors (i.e. the ‘ who’ , ‘ where’ and ‘ when’ of a theory (Whetten, 1989), which set the boundaries for the generalisation of a theory, also apply to Ugandan smallholder farmers’ intentions towards SPDC.

In the case of the use of ICT for research or data collection purposes, empirical evidence from previous studies supports the integration of a construct that takes into account the expected enjoyment of using the technology (Bosnjak et al., 2009; Dabholkar & Bagozzi, 2002; Moon & Kim, 2001). Rogelberg et al. (2001) state that anticipated enjoyment of technology-related survey scenarios should be conceptually consistent with the idea of general enjoyment of the survey. In other words, respondents who generally enjoy participating in surveys should ideally also enjoy participating in smartphone surveys (Bosnjak et al., 2009). Overall survey cooperation, including consent and low non-response, can predict respondents’ willingness (intention) to participate in mobile surveys (Jäckle et al., 2019). In this study, it is assumed that smallholder farmers who have intrinsic motivation (operationalised here as perceived enjoyment) for completing surveys or using mobile phones are likely to participate in the SPDC. In previous surveys using passive mobile data collection, participants’ attitudes and mobile phone (smartphone) use behaviours have been associated with their willingness to participate and actual participation (Di Matteo et al., 2018; Keusch et al., 2019). The likelihood of someone both expressing and implementing their willingness to participate is higher among those who regularly use mobile phones (Wenz et al., 2017). The use of information technology, including smartphones, requires the transmission of sensitive or confidential information about participants. Therefore, ensuring the security and protection of the transmitted data is of great interest to researchers in the social sciences such as psychology and sociology (Gefen et al., 2003). In situations such as this, it therefore seems useful to include a construct that encompasses perceived trustworthiness (PT) when assessing individuals’ intentions to participate in SPDC. PT in surveys refers to the anonymity, confidentiality and security of the data (Achyar & Setiawan, 2013). In times of looming uncertainty, trust is of particular importance. This is particularly evident with novel innovations and methods such as SPDC in resource-constrained areas. Smallholders may not trust the organization collecting the data or may be uncertain about the storage, transmission and use of their data.

In addition, previous research links technology acceptance and use to perceived costs (PC) and social influences such as subjective norms (SN) (Koloseni et al., 2021; Tiwari & Tiwari, 2020; Zainab et al., 2017). SN encompasses a person’s perception that most people who are important to them believe that they should or should not perform the behaviour in question (Ajzen & Fishbein, 1975). More specifically, SN refers to a change in a person's beliefs, feelings, attitudes, or actions brought about by social interactions with other people or groups (Tscherning & Mathiassen, 2010; Walker, 2015). Smallholders are simultaneously involved in a variety of networks, including with friends, family, other farmers and public and private organisations (Cofré-Bravo et al., 2019; Crespo et al., 2014; Gava et al., 2017). The decision of smallholder farmers to adopt certain behaviours, including SPDC, can therefore be influenced by these networks (Filippini et al., 2020). PC are the costs associated with using a technology or service, such as monetary and time costs (Masa'deh et al., 2013; Rind et al., 2017; Wu & Wang, 2005). Costs associated with SPDC include time spent completing surveys, smartphone prices, app downloads and subscriptions, credit and internet services, repairs, and battery costs. These costs are critical to farmers' perceptions that smartphone technology is expensive to use (Ronald Kabbiri et al., 2018), and therefore may directly impact their intention to use this technology to participate in surveys (Kuo & Yen, 2009). Previous research has shown that the intention to engage in a certain behaviour and the PC are negatively correlated (Chiu et al., 2017; Kuo & Yen, 2009).

According to the TAM extension proposed in this study (Figure 1), smallholders' intention to participate in SPDC is hypothesized to be influenced by three broad sets of factors. The first assumption is that the decision to engage in SPDC will be affected by factors that more broadly affect survey participation. For instance, intrinsic motivation (i.e., perceived enjoyment), extrinsic motivations such as PU, PEOU, and social-related influence (i.e., SN) along with positive attitudes will boost smallholders' intention to participate. However, cost-related considerations (PC) will lower participation intention. Secondly, trust considerations (i.e., PT) will be particularly important in shaping attitudes and participation intentions in survey situations involving smartphones. Thirdly, the smallholders' demographics, will influence their perceptions relating to different constructs in the proposed model.

This study's objectives extend beyond evaluating the proposed model; they also encompass determining the relative importance of the latent constructs in predicting smallholders' intention to participate in SPDC. Furthermore, the role of sociodemographic variables in differentiating smallholders' assessment of the model constructs was examined. Previous research on mobile phone use have produced mixed results regarding the influence of socio-demographic variables such as age and gender on technology adoption (Aparo et al., 2022). For example, some studies have found that women are equally likely to adopt new technologies in certain contexts, i.e. there was no significant difference between genders in the use of mobile phones (Filippini et al., 2020; Sáinz et al., 2014; Thar et al., 2021). Otene et al. (2018) reported a positive but non-significant effect of age on mobile phone use. These findings challenge the stereotypical view that certain demographic groups (e.g. women and older people) use technology less and less (Buccheri et al., 2011; Thar et al., 2021). Accordingly, validating these trends in a specific context (Uganda) among a less studied population group (smallholder farmers) is crucial as it reveals the generality or variability of such socio-demographic patterns across different population groups and regions. The use of the extended model in this study is considered useful as it allows the comparison of our findings with previous studies that have applied the TAM. Furthermore, the flexibility to add additional variables to the model increases the predictive power of the proposed model while allowing a deeper understanding of smallholder farmers' intention to participate in smartphone-based data collection. The findings may be of relevance to policy makers, researchers and stakeholders in the agricultural sector. In Figure 1 below, the hypotheses (relationships) tested in our extended TAM model are presented. A positive relationship between any two variables within the model is denoted by a plus (+) sign, indicating that an increase in one variable is expected to lead to an increase in the other. Conversely, a minus (-) sign denotes a negative relationship, meaning that an increase in one variable is expected to result in a decrease in the other. The detailed hypotheses are provided in annex 5.

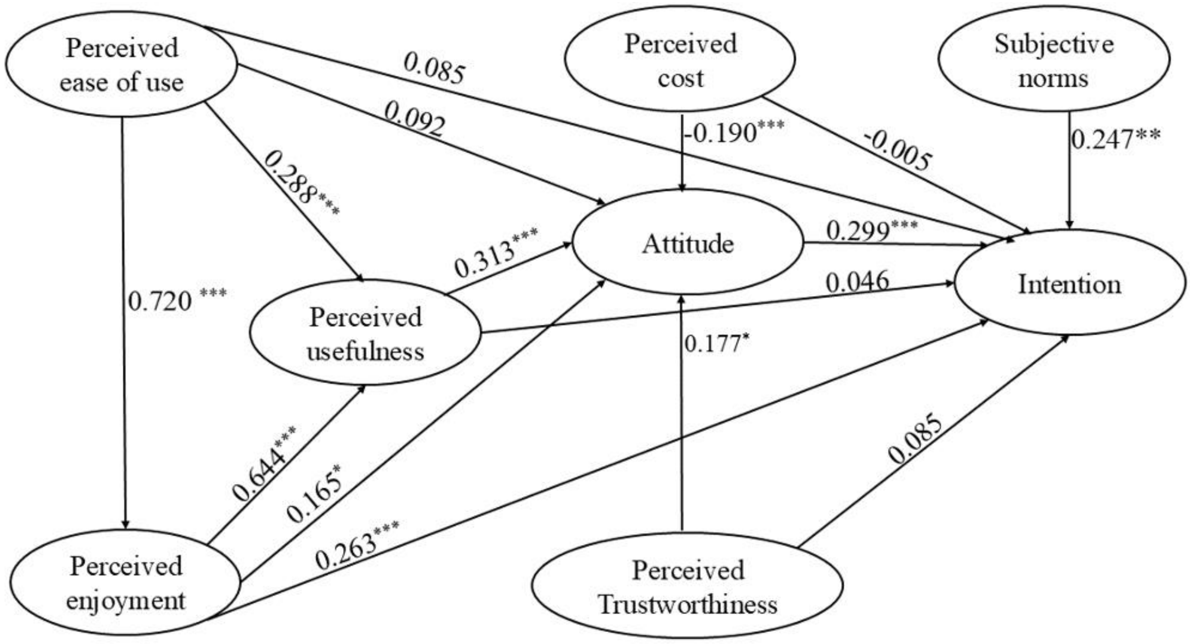

Figure 1: A theoretical structural model for intention to participate in smartphone-based data collection

2. **Materials and methods**

*2.1. **Questionnaire development and construct measurement***

The survey was programmed (created and deployed) online and later transferred to smartphones with a pre-installed survey app so that interviewers could access the questionnaires during data collection. Each interviewer had a unique identifier so that data submission could be tracked in real time and errors could be corrected almost immediately. The survey collected data on (1) socio-demographic characteristics (e.g. age, mobile phone ownership (MPO), previous participation in a survey (PSP), sex, age and education level) and (2) constructs of the extended TAM as antecedents for the intention to participate. MPO and PSP were measured as binary categorical variables requiring yes/no responses. To check the quality and validity of the survey questions and ensure that they were easy to understand, the questionnaire used was pretested and validated with a group of thirty farmers outside the study sites. The pre-test resulted in the removal of the statements '*I am worried about my data being shared with third parties if I answer the questionnaires via smartphones*' and '*I am not worried about the costs if I answer the questionnaires via smartphones*', which referred to PT and PC, respectively. The reason for this is that their inclusion in the measurements would affect the internal consistency reliability of the constructs. In addition, these deleted statements had the lowest correlation coefficient with the entire scales, so it was assumed that they were not measuring the same constructs as the other items under PT and PC. The wording of the items for SN and PT was also changed to facilitate understanding. A total of eight constructs were included in the final questionnaire, including PU (five items), PEOU (four items), PE (four items), PT (five items), PC (three items), ATT (four items), SN (four items) and INT (five items). The constructs and associated items were determined on the basis of previous studies and modified to ensure content validity. The order of the scales was randomised and the items within each scale were also presented in a randomised order. The items of each model construct were measured on a five-point Likert scale ranging from 'strongly disagree' (1) to 'strongly agree' (5). In contrast, the five-point scale for INT ranged from ' very unlikely' (1) to ' very likely' (5). Details of the wording of the items, the mean scores and the scales used can be found in annex 1.

2.2. ***Data collection***

This study was conducted in six sub-counties of Gulu district in Northern Uganda: Awach, Unyama, Palaro, Bungatira, Patiko and Paicho. These sub-counties were specifically selected because their inhabitants mainly practise smallholder agriculture, both arable farming (Tabuti et al., 2022) and livestock rearing (Alarakol et al., 2021) to earn a living. The target population of smallholder farmers was randomly and proportionally selected from each of the six sub-counties. The smallholder farmers were eligible to participate in the survey if they spoke either Acholi or English, resided in one of the designated study sites and were at least 18 years of age. A quantitative cross-sectional design was used to collect primary data from the smallholder farmers. While allowing participants to directly use smartphones to respond to the survey may have been an option, doing so would have introduced significant bias into the data. Previous research shows that smartphone ownership is more common among males and younger individuals, which would likely have led to the overrepresentation of these groups if participation were limited to smartphone users. To avoid this bias and ensure a more representative sample, we permitted non-smartphone users to participate by having research staff record their responses. This approach provided equal participation opportunities for all respondents, regardless of smartphone ownership, and ensured that our findings could be generalized to the broader population. Enumerators were trained on how to use the Surveyor application to conduct surveys and received instructions on basic troubleshooting, such as how to successfully submit completed surveys to the cloud. Data collection was possible offline, with submission occurring as soon as interviewers reached areas with an internet connection. Prior to being interviewed, each participant was required to give written, verbal or thumbprint consent, although no ethical review and approval was required for this study. In addition, all participant data and personal information was anonymised so that respondents could not be identified in the results of the study. The local authorities and the District Agricultural Officer in the study region were not only informed about the study, but also gave their consent and a letter of introduction. A total of 317 smallholder farmers were recruited to participate in the study.

2.3. ***Data analysis***

Following data cleaning, 306 responses were included for the analysis, with eleven respondents being eliminated due to missing data. In SPSS version 28, the variable age was recoded into five categories namely, ‘ 25 and under (i.e., ≤25),’ ‘ 26-35,’ ‘ 36-45,’ ‘ 46-55,’ and ‘ over 55. ‘similarly, education was recoded into a dummy variable as ‘ 0 = Uneducated’ and ‘ 1 = Educated.’ Descriptive statistics, including frequencies and percentages were computed to characterize the respondents. Multivariate analysis of variance (MANOVA) was used to determine between-group differences on the model variables namely PEOU, PU, PE, PT, PC, ATT, SN, and INT. The independent variables considered were MPO, age group, education, PSP, and sex. For the significant MANOVA tests, independent sample t-tests were conducted to determine where the differences existed with respect to education, MPO, PSP and sex. A post-hoc test, considering the Games-Howell criteria was performed to assess which groups differed with respect to age.

Partial Least Squares Structural Equation Modelling (PLS-SEM) was performed in SmartPLS 4 (Hair et al., 2019) to predict the constructs of the extended TAM model and explain how they are related to smallholder farmers' intention to participate in SPDC. As PLS-SEM combines multiple regression with component analysis and allows for the simultaneous examination of all relationships, it was considered the most appropriate technique for this study (Hair et al., 2019). PLS-SEM was particularly preferred for its ability to estimate complex models with multiple constructs, indicator variables and structural paths without requiring distributional assumptions for the data (Hair et al., 2019; Henseler et al., 2016; Joseph F. Hair et al., 2017). For items related to the model constructs, negatively worded sentences were reverse-coded in SPSS before PLS-SEM was performed.

In order to describe the relationship between the latent variables and their indicators, a reflective measurement model was specified and evaluated. The psychometric properties of the reflective measurement model were evaluated with regard to the reliability of the construct, the internal consistency of the construct and the construct validity. Once the reliability and validity of the reflective measurement models had been confirmed, the structural model was first analysed for possible collinearity problems, followed by an assessment of the significance and relevance of the relationships in the structural model. The explanatory and predictive power of the model was also assessed.

We also wanted to investigate whether there were differences in the relationships for certain demographic variables. However, assessing the measurement invariance of the composites using partial least squares (three-stage MICOM procedure) did not provide sufficient evidence to proceed with the multigroup analysis. According to the available studies, group comparisons using PLS-SEM can be misleading if the invariance of the measurements is not established by the researchers (Hair et al., 2024; Henseler et al., 2016)

3. **Results**

3.1. Smallholders' sociodemographic profile

As shown in Table 1, there were more female than male respondents, with 69% of respondents stating that they owned a mobile phone. The majority of respondents belonged to the age group ' 26-35' , followed by the age group ' 36-45' and those who were 25 years or younger. The presence of more female and younger respondents in the sample is representative of Uganda's young population and largely female-dominated smallholder agriculture (UBOS, 2016, 2020). This shows that, on average, the sample consisted of young smallholder farmers, as evidenced by the average age of 38 years. More than half of the respondents had at least a primary school qualification.

Table 1: Descriptive characteristics of respondents (N = 306)

Variable	Category	Frequency	Percentage (%)
Sex	Male	96	69
	Female	210	31
MPO	Owner	212	69
	Non-owner	94	31
Age group (years)	≤25	61	20
	26-35	86	28
	36-45	67	22
	46-55	42	14
	56 and older	50	16
EduGroup	Educated	188	61
	Uneducated	118	39
PSP	Yes	158	52
	No	148	48

Note: Mean age = 38 years; EduGroup = Education status; MPO = Mobile phone ownership; PSP = Previous survey participation

3.2. Between-group differences in construct assessment

With the exception of PSP, the results of the MANOVA in Table 2 show that there are statistically significant differences between the groups in the dependent variables (i.e. the constructs of the extended TAM model). Thus, the evidence is sufficient to reject the null hypotheses and conclude that respondents' PC, PEOU, PE, ATT, INT, SN, PT, and PU differed significantly by sex, MPO, educational status, and age group. The mean values for the different variables, i.e. PEOU, PU, PE, PT, PC, ATT, SN and intention to participate INT, are shown in the annex 2.

Table 2: Socio-demographic differences in the means of constructs (MANOVA)

Variable	Pillai Trace	F	df1	df2	Sig.	Partial Eta Squared
Sex	0.075	3.014b	8	297	0.003	0.075
PSP	0.047	1.820b	8	297	0.073	0.047
MPO	0.112	4.669b	8	297	<.001	0.112
EduGroups	0.11	4.605b	8	297	<.001	0.11
AgeGroup	0.161	1.553	32	1188	0.026	0.04

Df = degree of freedom, df1 = Hypothesis df, df2 = Error df, AgeGroup = Age group, EduGroup = Education status, MPO = Mobile phone ownership, PSP = Previous survey participation

Following the significant MANOVA results, an independent samples t-test was conducted to determine where differences exist between groups (age, sex, education, MPO) on the model constructs. Mean scores for PEOU were statistically significantly higher for respondents who are male, i.e. t (194.9) = 2.333, p = 0.021, educated (t (214.773) = -4.544, p < 0.001) and owned a mobile phone (t(146.487) = 4.531, p<.001). The mean intention to participate was significantly higher among male respondents (t (232.4) = 3.351, p<0.001) and among those who owned a mobile phone (t (299) = 4.030, p <.001). Mean PU was significantly higher among respondents who owned a mobile phone (t (299) = 3.265, p = 0.001) and are educated (t (205.817) = -3.236, p = 0.001). Similarly, respondents who are educated (t (212.526) = -2.347, p = 0.02) and owned a mobile phone (t(299) = 3.006, p = 0.003) had significantly higher mean scores for subjective norms. The mean score of PE was significantly higher among educated respondents (t (209.020) = -2.765, p = 0.006). The mean score of PC (t(299) = -2.922, p = 0.004) was statistically higher among non-mobile phone owners. PT (t(137.757) = 2.635, p = 0.009) and attitude (t(299) = 3.581, p <.001) had significantly lower mean scores for non-mobile phone owners. The detailed results can be found in the annex 3.

There were significant differences between respondents in the different age groups (see annex 4 for details). The Games-Howell post-hoc test revealed that (1) the mean difference in PEOU was significant in all age groups but was greatest between the youngest (≤25) and oldest respondents (over 55); (2) compared to respondents over 55 and respondents in the 36-45 age group, respondents who were ≤25 years old reported significantly higher PE and PU. In addition, the mean difference in attitude between the youngest respondents (≤25) and middle-aged respondents (36-45) was statistically significant, with the former having higher mean scores, indicating a more positive attitude.

3.3. Measurement model assessment

The two measures of construct reliability analysed were Cronbach's alpha (α) and composite reliability (rho_c). The values for both criteria are above the recommended value of 0.7, which indicates satisfactory internal consistency reliability and construct reliability. Construct validity was assessed on the basis of convergent validity and discriminant validity. Convergent validity was assessed using the average variance extracted (AVE), and all values are above the minimum acceptable value of 0.5 (Hair et al., 2021). With the exception of PC, most constructs had above average mean agreement with the items (see annex 1 for item means). Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) criteria of Henseler et al. (2015). All HTMT values are within the recommended threshold of 0.900 and below, so that discriminant validity is established. The mean values as well as the reliability and validity statistics for the model constructs (Table 3) and the results of the discriminant validity (Table 4) are presented below.

Table 3: Means, reliability, and convergent validity statistics per construct

Construct	Mean	SD	α	rho_c	AVE
Perceived ease of use	3.83	1.14	0.92	0.94	0.91
Perceived enjoyment	3.90	1.05	0.91	0.93	0.82
Perceived usefulness	4.08	1.01	0.92	0.93	0.80
Perceived trustworthiness	4.15	0.96	0.89	0.92	0.73
Subjective norm	4.08	0.98	0.87	0.91	0.72
Perceived cost	2.18	1.10	0.75	0.85	0.66
Attitude	4.16	0.77	0.87	0.91	0.72
Intention	4.03	1.00	0.94	0.94	0.92

SD, Standard deviation

Table 4: Test of discriminant validity (HTMT criterion)

	ATT	INT	PC	PE	PEOU	PT	PU	SN
ATT								
INT	**0.835**							
PC	0.678	**0.591**						
PE	0.774	0.786	**0.512**					
PEOU	0.724	0.702	0.585	**0.757**				
PT	0.757	0.709	0.679	0.705	**0.688**			
PU	0.824	0.804	0.596	0.900	0.793	**0.760**		
SN	0.749	0.762	0.685	0.685	0.620	0.678	**0.741**	

ATT = Attitude; INT = Intention; PC = Perceived Cost; PE = Perceived Enjoyment; PEOU = Perceived ease of use; PT = Perceived trustworthiness, PU = Perceived Usefulness; SN = Subjective Norm

3.4. Structural model assessment

The structural model fit was assessed using the predictive relevance (Q^2) of the endogenous constructs, the standardized root mean squared residual (SRMR) and the value inflation factor (VIF). All these metrics (Table 5) had values below the recommended thresholds, indicating a satisfactory model fit. The model explained 71.9% of the variance in respondents' intention to participate.

Table 5: Structural model Fit indices

Latent variable	Adj. R^2	Q^2	VIF	SRMR
ATT	0.630	0.546	1.807	
INT	0.719	0.613	1.612	
PU	0.763	0.546	2.540	
PE	0.517	0.586	1.888	
Goodness-of-fit measure		0.052		

ATT = Attitude, INT = Intention, PE = Perceived Enjoyment, PU = Perceived usefulness, Q^2 = predictive relevance, VIF = value inflation factor, SRMR = standardized root mean squared residual, Adj. R^2 = Adjusted R-squared

After the fit of the structural model was assessed, the path coefficients were analysed. For the direct effects, attitude is the strongest predictor of intention to participate in SPDC, followed by PE and SN. The direct positive predictors of attitude towards SPDC are PU, PE and PT. PC also has a direct influence on attitude, albeit in a negative way. PEOU has a direct positive and significant influence on PU and PE. The exact beta values and significance levels for all variables can be found in Figure 2. The model also has indirect effects, as shown in Table

6. Thus, the total effect (both direct and indirect) of all constructs on the intention to participate is 0.57 (the sum of the product of the coefficients). In summary, hypotheses H1a, H1b, H2a, H2b, H2c, H3a, H4a, H5, H6a, H6b and H7 were supported while the remaining hypotheses were not confirmed.

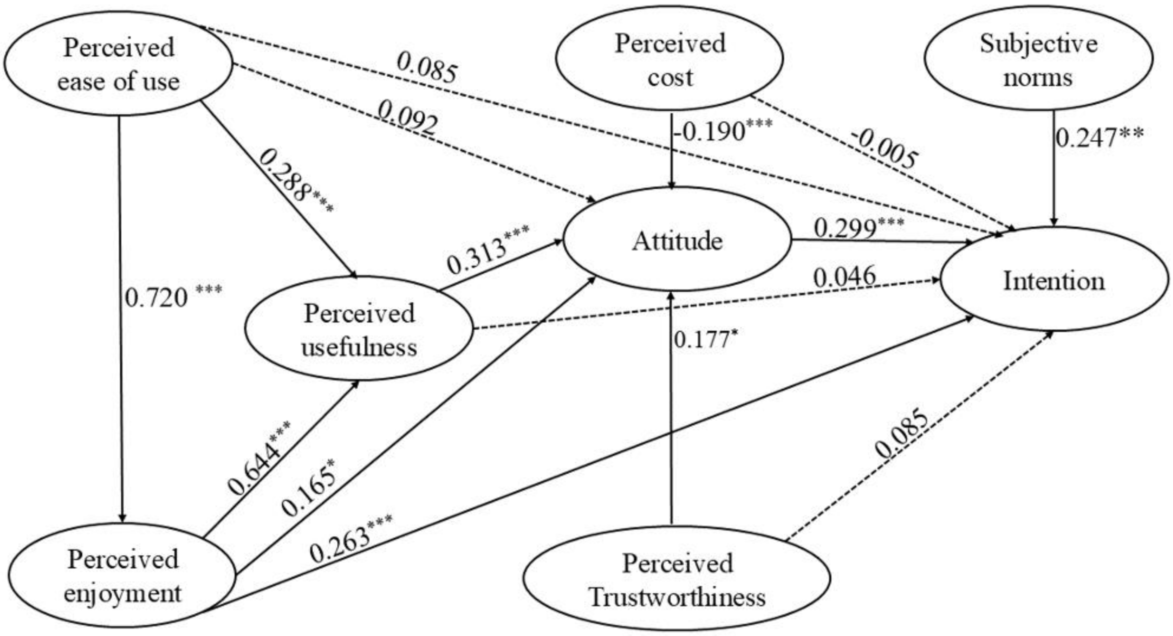

Figure 2: Structural model of smallholders' intention to participate in smartphone-based data collection with standardized path coefficient (N = 306)

*Note: The dashed arrows represent insignificant paths, whereas solid arrows indicate significant relationships. **p < 0.05; ***p < 0.001.*

Table 6: Indirect model effects

Specific indirect paths	Product of coefficients	p values
PEOU -> PU -> ATT -> INT	0.026	0.022
PC -> ATT -> INT	-0.057	0.004
PU -> ATT -> INT	0.093	0.007
PEOU -> PE -> ATT -> INT	0.035	0.050
PEOU -> ATT -> INT	0.029	0.164
PT -> ATT -> INT	0.053	0.040
PEOU -> PE -> INT	0.191	0.000
PE -> PU -> ATT -> INT	0.060	0.007
PEOU -> PE -> PU -> ATT -> INT	0.043	0.008
PEOU -> PE -> PU -> INT	0.021	0.001
PE -> ATT -> INT	0.049	0.050
PE -> PU -> INT	0.029	0.001

ATT = Attitude, INT = Intention, PC = Perceived Cost, PE = Perceived Enjoyment, PEOU = Perceived ease of use, PT = Perceived trustworthiness, PU = Perceived Usefulness, SN = Subjective Norm

4. Discussion

This study fills a knowledge gap in the existing literature by providing an understanding of the variables that influence Ugandan smallholder farmers' intention to participate in smartphone-based surveys. Overall, the smallholder farmers surveyed have a positive attitude toward SPDC as indicated by the high average scores for the willingness to participate (M = 4.03, SD = 1.00). This willingness or intention to participate is determined by a number of factors, which are explained below.

4.1. The role of sociodemographic variables

In general, female, uneducated, non-mobile phone-owning and older respondents had lower mean scores than male, educated, younger and mobile phone-owning respondents on all constructs except PC. According to the triple hurdle concept established by Asravor et al. (2021), owning a mobile phone is the first critical hurdle to using a mobile phone that creates the desire and ability to learn about mobile phone products, features and services. Similarly, access to or ownership of a smartphone has been identified as the first barrier to SPDC participation (Couper et al., 2018; Keusch et al., 2022). Greater product knowledge, experience, skills and abilities in using mobile phones could be the reasons for the better mean scores for most constructs among mobile phone owners and the educated (Aparo et al., 2022; Ogbeide et al., 2015).

Some of the socio-demographic differences between mobile phone owners and non-owners appear to have narrowed over time (Center, 2019; Keusch et al., 2022). However, owners differ in important variables and tend to be younger (Jäckle et al., 2019; Keusch et al., 2020). Even among mobile phone owners, some are more likely to participate in SPDC than others (Keusch et al., 2022). Consistent with the findings of previous research, this study found that respondents who are willing to participate in SPDC tend to be younger (Mate et al., 2023; Sagvari et al., 2021; Verzosa et al., 2020) and more educated (Bell et al., 2019; Keusch et al., 2020). In contrast to some earlier research (Keusch & Yan, 2017) and in line with others (Bell et al., 2019; Keusch et al., 2020; Keusch et al., 2019; Ochoa Gómez, 2022), the findings of this study suggest that male respondents were more willing to join the SPDC, as evidenced by their higher average intention to participate scores. Unlike previous studies (e.g., Bosnjak et al., 2009), previous survey participation was not a significant differentiating variable for respondents' evaluation of key model constructs.

4.2. Direct and indirect antecedents

PE, attitude (ATT) and SN are the direct explanatory variables for the behavioural intention to participate in SPDC, with attitude being most predictive for behavioural intention. In other words, smallholders are more likely to have the intention to participate in SPDC if they perceive hedonic values, the support and approval of their significant others, and have a positive attitude towards SPDC. Consistent with the literature and behavioral theories (i.e. TAM, TPB and TRA), this study found that participants who reported having a positive attitude also had a positive intention to participate in SPDC (Ajzen & Fishbein, 1975; Chuang et al., 2020; Li et al., 2019; Meijer et al., 2014). The positive influence of PE on the intention to participate in SPDC is supported by previous research on the role of intrinsic motivation (Alalwan et al., 2018; Bosnjak et al., 2009). Similarly, the positive influence of subjective norm is consistent with previous research on mobile phone use and adoption (Abbas, 2016; Gauld & Reeves, 2023; Irawan & Hurriyati 2020).

Although PU, PEOU, PT and PC did not have a direct influence on smallholder farmers' intention to participate in SPDC, they did have an indirect influence on intention. The fact that SPDC is still relatively new in rural LICs could be an explanation for these negligible direct effects. It is plausible that farmers lack the necessary experience to form an opinion about these concepts strong enough to directly influence their intention to participate. However, the relationship between PEOU and intention to participate becomes positive and significant when mediated by PE. In addition, PEOU also has a positive and significant indirect effect on intention to participate when the relationship is mediated by (1) both PU and ATT, (2) both PE and ATT, or (3) PE, PU, and ATT together. The lack of association between cost perception and behavioural intention to participate in SPDC is consistent with the results of previous studies (Bosnjak et al., 2009; Tiwari & Tiwari, 2020). The influence of PT, PU and PC on intention to participate is mediated by smallholder farmers' attitudes towards SPDC. Previous studies on the adoption and use of smartphone technologies (Bosnjak et al., 2009; Ronald Kabbiri et al., 2018; Keusch et al., 2019; Ochoa Gómez, 2022; Wenz et al., 2017, 2019) have generally confirmed the positive influence of PU, PE and PT on attitude, which was also found in the current study. PC had a significant and negative impact on attitude, which is consistent with previous research showing a negative correlation between attitude and cost perception (Tiwari & Tiwari, 2020; Zainab et al., 2017). The insignificant relationship between PEOU and ATT was rather surprising, although Sánchez-Prieto et al. (2017) also reported a similar result. Furthermore, these results suggest that the influence PU mediates the influence of PEOU on ATT. This is in line with the TAM, which proposes that the perception of effort required for a behaviour contributes to the formation of positive attitudes and intentions by reinforcing the perception of benefits (Davis, 1985; Sorce & Issa, 2021). Therefore, PEOU could only have an influence on ATT if it also has an influence on PU.

4.3. Guidelines for persuading farmers to engage in SPDC

Building on the findings of this study, which are critical to promoting smallholder participation in SPDC, we propose and advocate for the following actions.

First, communication/messaging that emphasizes the benefits of participating in SPDC, coupled with persuasive appeals, can be a key strategy to improve smallholder farmers' attitudes and thus their intention to participate in SPDC (Bosnjak et al., 2009). In implementing SPDC, scientists, extension workers and other actors in the agricultural sector should consider reaching out to smallholder groups and communities, as empirical expectations regarding what others do and normative expectations regarding what others approve of, measured in this study as SN, seem to play a crucial role in the decision to participate in SPDC (Angerer et al., 2024). Previous research has shown that farmers tend to rely on these types of groups for support, knowledge and information by utilising the wealth of experience and skills of these groups (Filippini et al., 2020).

Secondly, app developers could consider developing features that increase the hedonic value of smartphones. Similarly, researchers might consider designing SPDC surveys in formats and ways that make them more enjoyable, whether that be in the form of images, text, videos or enhancing the overall survey experience.

Thirdly, the perception of effort required to use smartphones for data collection is significantly associated with PE and PU. Chua et al. (2018) find that potential users are less willing to use sophisticated technologies. Therefore, efforts to improve PEOU would be another important strategy that app developers and researchers could utilise to increase SPDC adoption among smallholder farmers. Such strategies, including targeted training, should emphasise the benefits of smartphone technologies, enhance smallholder farmers 'skills and capabilities, and improve their access to certain support services, such as low-cost mobile internet connections (Ahikiriza et al., 2022). Further enhancing PEOU through the development of mobile apps with a user-friendly interface could be another strategy that app developers could utilise to increase the overall adoption of mobile apps and technologies in smallholder farming communities in LICs such as Uganda (Ahikiriza et al., 2022; Michels et al., 2019). On the researchers' side, demonstrations or providing objective information to smallholder farmers before participating in surveys could also be helpful in improving PEOU.

However, care should be taken to ensure that such demonstrations and information do not lead to bias. Although PEOU had the lowest average score in the overall sample, our results showed that the average PEOU was even lower among women, uneducated individuals, non-mobile phone owners, and older respondents. Therefore, strategies to improve perceptions of ease of use should take into account this gender and socio-demographic difference in perceptions to effectively increase willingness to participate in SPDC among smallholder farmers.

Fourthly, access to a smartphone is a prerequisite for participation in the SPDC (Couper et al., 2018; Keusch et al., 2022). Policymakers in the agricultural sector could incentivise smartphone ownership among smallholder farmers by working with device manufacturers to provide smartphones and apps to smallholder farmers at a subsidised cost. This could remove the ownership barrier, improve farmers' perceptions of the costs associated with participating in SPDC and improve their attitudes, especially among older, uneducated and female respondents without mobile phones. Previous research shows that unconditional incentives are preferable to conditional incentives when it comes to increasing SPDC usage (Wenz & Keusch, 2023).

Finally, when designing and implementing smartphone-based surveys, researchers should consider giving smallholder farmers the opportunity to review the data collected prior to submission. Clear information about the purpose of data collection and how and where the data will be stored can help smallholder farmers perceive the data as trustworthy and develop a positive attitude towards the SPDC (Beierle et al., 2019).

4.4. Limitations and future research perspectives

There are some limitations to this study that need to be considered with regard to the generalisability of the results.

The respondents were asked to self-report their intention to participate in this type of data collection, rather than observing their participation behaviour in a real smartphone-based study. Social desirability bias can occur when farmers are asked directly about their motives and determinants of their decisions, including the extent of influence of significant others (Dessart et al., 2019). Given the likelihood of socially desirable responses in the self-reports (Gier-Reinartz & Harms, 2024), it is possible that the high mean scores for intention were partly influenced by social desirability bias. Therefore, as a complement to the self-reports used in this study to measure smallholder farmers' intentions to participate in SPDC, future studies might consider more observational or experimental approaches that measure actual willingness to perform various data collection tasks, such as downloading survey apps, submitting daily or weekly agricultural performance reports, and completing surveys (Revilla et al., 2019). Experimental or observational studies can help to solve problems related to self-reported measurements (Dessart et al., 2019). To reduce bias in self-reported data, future research efforts could use (1) qualitative approaches as suggested by Blattman et al. (2016), (2) quantitative survey techniques such as randomised responses (Blair et al., 2015; Warner, 1965) and the endorsement experiment (Bullock et al., 2017) or the list experiment method to indirectly solicit opinions on specific technologies or behaviours from respondents (Eriksen et al., 2017). In addition, the assessment of such bias may involve the use of established scales such as the Marlowe-Crowne Social Desirability Scale (Di Noia et al., 2016) or that of Kemper 2012 (Gier-Reinartz & Harms, 2024).

Additionally, given the initial results of this cross-sectional study and the finding that the smallholder farmers are generally willing to participate in SPDC, future research could investigate whether this intention translates into actual behaviour as postulated by TAM, TPB and TRA. Studies have shown that people often suffer from an intention-behaviour gap (Bhattacherjee & Sanford, 2009; Conner & Norman, 2022; Koole et al., 2023). By using longitudinal studies, future studies can track changes in farmers' intentions and behaviour over time (Lamb et al., 2020). This is important to understand how the factors investigated in this study evolve, especially as they could be influenced by external variables such as technological advances, policy changes or personal experiences (Ajibade, 2018). Furthermore, the combination of experimental and longitudinal approaches would enable future researchers to better identify and infer causal relationships between farmers' intentions and behaviour, i.e. to determine whether and how changes in intentions lead to changes in behaviour (i.e. actual participation) or vice versa (Dessart et al., 2019).

Previous research has shown that incentives, feedback and training can increase willingness to participate in SPDC (Keusch et al., 2019; Wenz & Keusch, 2023). This needs to be further investigated in future studies on smallholder farmer participation in SPDC. In addition, such studies should attempt to differentiate the effects of different types of incentives.

This study targeted smallholder farmers in Northern Uganda. The sample consists mainly of female and young respondents with relatively little technological experience. Although women dominate smallholder agriculture in LICs (Twinorugyendo, 2019; Yuhang et al., 2023), and Uganda's population is predominantly young (UBOS, 2020), regional differences in technological, social and skill access to smartphone technologies in Uganda may mean that this sample does not accurately represent all regions of Uganda. A follow-up study in other regions of Uganda may be worthwhile to increase the validity of the results.

5. Conclusion

In recent years, the use of SPDC methods in the social sciences has increased. Researchers are now able to collect data actively or passively on people's perceptions, beliefs and behavioural intentions. In Uganda, SPDC is a relatively new technological advance that can be utilised by universities and agricultural sector actors to improve not only research and agricultural outcomes, but also development outcomes. Previous studies that have investigated data collection using mobile apps for populations other than farmers have shown that they are not well-accepted. This study is the first to assess smallholder farmers' intention to participate in SPDC in the context of LMICs. It provides empirical evidence specific to smallholder farmers in Uganda, a stakeholder group and geographical focus that is often underrepresented in the existing literature. To this end, the TAM extension examined here has proven useful as it distils the SPDC participation process into core components and provides a clear framework that can be easily applied to improve smallholder SPDC participation. By identifying specific factors that influence participation, this work creates actionable knowledge that can inform future research and practise in agricultural data collection and technology dissemination.

These findings also have practical implications for the design and implementation of SPDC initiatives in Uganda. The finding that younger people are more likely to participate allows researchers, application developers, agricultural program implementers and extension workers to target this population more strategically and potentially use them as early adopters or advocates of SPDC. Conversely, identifying the lower likelihood of women's participation may highlight a critical area for intervention. This finding can guide the development of gender-specific approaches that address specific barriers for women to encourage wider participation in SPDC. It is crucial for future researchers to be mindful of both sampling strategies and survey design when implementing SPDC. Our results have shown that younger people are more inclined to participate in SPDC, while females demonstrate less interest compared to males. This creates a potential risk of underrepresentation of women and overrepresentation of younger males in the collected data if smartphones are the primary mode of data collection. To mitigate this, researchers should employ a stratified sampling method – selecting respondents based on demographic variables such as age and gender to ensure a balanced and representative sample. Beyond sampling, survey design should also be tailored to accommodate the preferences and accessibility challenges of different demographic groups. For example, providing alternative modes of data collection or designing smartphone interfaces that are more inclusive could improve participation from underrepresented groups, such as older individuals or women. These combined strategies, i.e. thoughtful sampling and inclusive survey design will ensure more accurate, representative data and help future researchers address potential biases in SPDC procedures.

The results of in this study suggest that all stakeholders interested in the use of mobile phones in general and smartphones specifically for research among smallholder farmers should consider the dimensions of ATT, SN, PE, PU, PEOU, PC, and PT when utilising SPDC.

Data collection via smartphone is widely recognised for its reliability, convenience and reduced susceptibility to errors. However, it is important to note that smartphone data collection is not a panacea that will make up for a poor or badly designed survey. If the survey is poorly designed, the results will be unreliable or invalid, regardless of the method of data collection. Therefore, researchers who choose to use SPDC must prioritise the design of high-quality survey instruments and ensure that the content and scales are robust and meaningful. The relevance of the topic and content of the survey is also critical as it directly impacts participant engagement and the overall success of the data collection.

The ability to engage smallholder farmers and other agricultural actors in SPDC is critical to maximising their potential for research, the agricultural sector and development in LMICs. The results of this study shed light on how this can be achieved.

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NOA: Conceptualization, data curation, investigation, formal analysis, methodology, writing-original draft, writing, review, editing, Funding acquisition**; BD**: Methodology, Writing-original draft, writing, review, and editing; **WO:** Writing, review, and Supervision; **HDS:** Conceptualization, methodology, writing, review and editing, Funding acquisition, supervision

Declaration of interest statement

The authors report there are no competing interests to declare.

Data availability statement

Data will be made available on request.

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Ethical approval statement

According to local legislation, the study involving human subjects did not require ethical review or permission because all the data was anonymised.

Informed consent statement

Informed oral, written and thumbprint consent was given by each study participant to take part in the survey.

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Annexes

Annex 1: Detailed item wordings and means per construct of the proposed model

Construct	Item code	Mean ± Standard deviation	Item wording	Words partly adapted from
Perceived usefulness (PU)	PU 1	4.05 ± 1.02	It would be convenient if I could respond to surveys with a smartphone.	(Bosnjak et al., 2009; Davis, 1989)
	PU 2	3.96 ± 0.95	By having the opportunity to fill out questionnaires using a smartphone, I could choose the location from which to respond	
	PU 3	4.17 ± 1.01	Participating in surveys via smartphones will be beneficial for me.	
	PU 4	3.99 ± 1.04	When offered the chance to take part in a smartphone-based data collection, I would be more accommodating in terms of choosing when I respond.	
	PU 5	4.23 ± 1.04	Data collection through smartphones would enable me to participate quickly.	
Intention	INT 1	4.16 ± 1.00	When requested to participate in smartphone-based data collection, I would do so very likely	(Ajzen, 2006; Bosnjak et al., 2009; Lu et al., 2008)
	INT 2	4.06 ± 0.96	I would be willing to participate in smartphone data collection	
	INT 3	4.12 ± 0.95	I would be willing to complete a survey questionnaire using a smartphone.	
	INT 4	3.76 ± 1.18	I would intend to participate in smartphone-based data collection	
	INT 5	4.09 ± 0.93	I can imagine participating in smartphone-based data collection	
Perceived Cost (PC)	PC 1	2.47 ± 1.30	I think that it would be costly to answer questionnaires using a smartphone	Bosnjak, Porter and Donthu (2006)
	PC 3	1.99 ± 1.11	I think that the costs of answering questionnaires using smartphones would be burdensome to me	
	PC 4	2.09 ± 0.88	I am not sure about the exact cost of participating in smartphone data collection would cost me	
Perceived	PT 1	4.19 ± 0.92	I am concerned about the confidentiality and anonymity of my data when answering questionnaires using a smartphone	(Bosnjak et al., 2009; Lu et al., 2008)

trustworthiness (PT)	PT 2	4.02 ± 1.15	Due to appropriate technical measures, my data are well protected when I answer questionnaires using smartphones	
	PT 3	4.12 ± 0.92	Data collection through a smartphone is not trustworthy	
	PT 4	4.15 ± 0.90	Using smartphones for conducting surveys can be a secure method of collecting data	
	PT 5	4.29 ± 0.92	I am confident my data will be used appropriately when I respond to questionnaires using a smartphone	
Attitude (ATT)	ATT 1	4.16 ± 0.84	Smartphone-based data collection provides a practical way to participate in surveys.	(Ajzen, 2006; Bosnjak et al., 2009; Childersa et al., 2001; Voss et al., 2003)
	ATT 2	4.23 ± 0.71	Participating in smartphone-based data collection would be pleasant	
	ATT 3	4.25 ± 0.73	Participating in smartphone-based data collection would be negative	
	ATT 4	4.00 ± 0.80	Participating in smartphone-based data collection would be good	
Perceived enjoyment (PE)	PE 1	4.04 ± 1.04	It would be fun for me to fill out questionnaires using a smartphone	(Bosnjak et al., 2009; Childersa et al., 2001; Voss et al., 2003)
	PE 2	3.91 ± 0.98	Filling out questionnaires using a smartphone would be interesting to me	
	PE 3	3.72 ± 1.15	Participating in research and answering survey questions using a smartphone is not an exciting experience for me	
	PE 4	3.93 ± 1.04	I would not feel good when filling questionnaires on a smartphone.	
Subjective Norm (SN)	SN 1	4.16 ± 1.02	Most people whose opinion I value would very likely participate in smartphone-based data collection.	(Ajzen, 2006; Bosnjak et al., 2009)
	SN 2	4.00 ± 0.99	People who are important to me would not recommend that I participate in the smartphone-based data collection	
	SN 3	3.92 ± 0.90	I will participate in smartphone-based data collection because most people in my network would do it	
	SN 4	4.22 ± 1.00	I will not fill in smartphone-based survey because people whose opinion I value would not approve of it.	
Perceived ease of use (PEOU)	PEOU 1	3.85 ± 1.13	It would be easy to learn how to answer questionnaires using a smartphone	(Bosnjak et al., 2009; Davis, 1989)
	PEOU 2	3.86 ± 1.11	I am confident in answering smartphone- based surveys	
	PEOU 3	3.72 ± 1.16	It is not clear and understandable how to use smartphones for surveys	
	PEOU 4	3.90 ± 1.14	I would be quickly competent in filling out questionnaires using a smartphone	

Annex 2: Means of the model constructs per sociodemographic grouping variable

	Sex		Education		MPO		Age group				
Construct	M	F	0	1	O	NO	≤ 25	26-35	36-45	45-55	56 and older
PEOU	4.03 (0.98)	3.74 (1.04)	3.49 (1.11)	4.05 (0.92)	4.00 (0.96)	3.40 (1.1)	4.30 (0.69)	3.90 (1.00)	3.66 (1.05)	3.65 (1.16)	3.51 (1.11)
PU	4.17 (0.89)	4.04 (0.91)	3.86 (1.02)	4.22 (0.80)	4.18 (0.87)	3.82 (0.94	4.39 (0.62)	4.13 (0.87)	3.95 (0.96)	4.05 (1.00)	3.82 (0.99)
PE	4.01 (0.95)	3.90 (0.95)	3.7 (1.06)	4.02 (0.85)	3.95 (0.90)	3.75 (1.06)	4.20 (0.68)	3.95 (0.90)	3.76 (1.00)	3.83 (1.10)	3.70 (1.040
PC	2.18 (0.90)	2.19 (0.91)	2.21 (0.88)	2.17 (0.92)	2.08 (0.91)	2.42 (0.88)	2.02 (0.69)	2.28 (0.95)	2.24 (1.02)	1.97 (0.91)	2.33 (0.85)
PT	4.13 (0.86)	4.16 (0.80)	4.07 (0.9)	4.2 (0.76)	4.23 (0.75)	3.94 (0.94)	4.28 (0.77)	4.16 (0.76)	4.06 (0.89)	4.07 (0.92)	4.16 (0.78)
ATT	4.27 (0.74)	3.93 (0.95)	4.08 (0.74)	4.21 (0.59)	4.24 (0.62)	3.96 (0.69)	4.36 (0.49)	4.15 (0.63)	4.04 (0.75)	4.15 (0.69)	4.11 (0.65)
SN	4.15 (81)	4.04 (0.84)	3.93 (0.92)	4.17 (0.75)	4.17 (0.78)	3.86 (0.91)	4.28 (0.66)	4.12 (0.76)	3.92 (0.90)	4.00 (1.06)	4.02 (0.76)
INT	4.27 (0.74)	3.93 (0.95)	3.91 (1.02)	4.12 (0.82)	4.17 (0.85)	3.72 (0.96)	4.26 (0.70)	4.10 (0.86)	3.88 (0.97)	3.95 (0.97)	3.94 (0.97)

Note: M = Male, F= Female, Education (0 = Uneducated, 1= Educated), MPO = Mobile phone ownership (O = Owner, NO = Non-owner), numbers inside the bracket are Standard deviations of the corresponding mean

Annex 3: Sociodemographic association with Model constructs by independent samples t test

		t-test for Equality of Means			
Demographic variable	Construct	t	df	Sig. (2-tailed)	Mean Difference
Sex	PEOU	2.333	194.9	0.021	0.288
	INT	3.351	232.4	<.001	0.337
Mobile phone ownership	PEOU	4.531	146.487	<.001	0.606
	PU	3.265	299	0.001	0.367
	PT	2.635	137.757	0.009	0.295
	SN	3.006	299	0.003	0.312
	PC	-2.922	299	0.004	-0.331
	ATT	3.581	299	<.001	0.289
	INT	4.03	299	<.001	0.45
Education	PEOU	-4.544	214.773	<.001	-0.556
	PE	-2.765	209.02	0.006	-0.321
	PU	-3.236	205.817	0.001	-0.356
	SN	-2.347	212.526	0.02	-0.237

Note: df = degree of freedom, the mean difference is significant (sig.) at the 0.05 level, PEOU = Perceived ease of use, INT = Intention, PU = Perceived usefulness, PT = Perceived trustworthiness, SN = Subjective norm, PC = Perceived cost, ATT = attitude, PE = Perceived Enjoyment

Annex 4: Comparisons of the model constructs by age group (ANOVA)

Dependent Variable	(I) AgeGroup	(J) AgeGroup	Mean Difference (I-J)	Std. Error	Sig.
PEOU	≤25	26-35	.3893*	0.13955	0.047
		36-45	.6425*	0.15573	<.001
		46-55	.6444*	0.19902	0.016
		56 and older	.7942*	0.18046	<.001
	26-35	≤25	-.3893*	0.13955	0.047
	36-45	≤25	-.6425*	0.15573	<.001
	46-55	≤25	-.6444*	0.19902	0.016
	56 and older	≤25	-.7942*	0.18046	<.001
PE	≤25	36-45	.4359*	0.15046	0.036
		56 and older	.5058*	0.17125	0.033
	36-45	≤25	-.4359*	0.15046	0.036
	56 and older	≤25	-.5058*	0.17125	0.033
PU	≤25	36-45	.4314*	0.14199	0.024
		56 and older	.5636*	0.16155	0.007
	36-45	≤25	-.4314*	0.14199	0.024
	56 and older	≤25	-.5636*	0.16155	0.007
ATT	≤25	36-45	.3192*	0.11149	0.039
	36-45	≤25	-.3192*	0.11149	0.039

PEOU = Perceived ease of use, PE = Perceived Enjoyment, PU = perceived usefulness, ATT = Attitude, mean difference is significant (sig.) at 0.05 level, Std. Error = Standard Error

Annex 5: The hypotheses tested in our proposed model and the results

Construct	Hypothesis	Result
Perceived ease of use	H1a (+): Perceived ease of use has a positive effect on perceived enjoyment.	Supported
	Perceived ease of use has a positive effect on perceived usefulness.	Supported
	H1c (+): Perceived ease of use has a positive effect on attitude.	Not Supported
	H1d (+): Perceived ease of use has a positive effect on intention	Not supported
Perceived enjoyment	H2a (+): Perceived enjoyment has a positive effect on perceived usefulness.	Supported
	H2b (+): Perceived enjoyment has a positive effect on attitude.	Supported
	H2c (+): Perceived enjoyment has a positive effect on intention.	Supported
Perceived usefulness	H3a (+): Perceived usefulness has a positive effect on attitude.	Supported
	H3b (+): Perceived usefulness has a positive effect on intention.	Not supported
Perceived trustworthiness	H4a (+): Perceived trustworthiness has a positive effect on attitude.	Supported
	H4b (+): Perceived trustworthiness has a positive effect on intention. Attitude	Not supported
Attitude	H5a (+): Attitude has a positive effect on intention.	Supported
Perceived cost	H6a (-): Perceived cost has a negative effect on attitude.	Supported
	H6b (-): Perceived cost has a negative effect on intention.	Supported (Not significant)
Subjective norms	H7 (+): Subjective norms have a positive effect on intention.	Supported