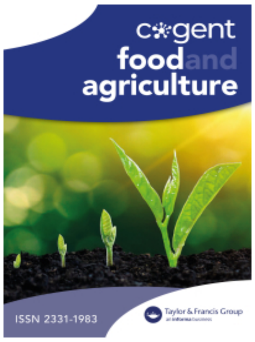

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Understanding perceived performance impacts of mobile phone use among smallholders in Uganda: the influence of task-technology fit and current use

Nathaline Onek Aparo[a,b], Alice Onek Atimango[a], Walter Odongo[b] and Hans De Steur[a]

[a]Division of Agri-Food Marketing and Chain Management, Department of Agricultural Economics, Ghent University, Ghent, Belgium; [b]Department of Rural Development and Agribusiness, Gulu University, Gulu, Uganda

ABSTRACT

This study evaluated the factors influencing the perceived performance impact (PPI) of mobile phone use in agriculture. Based on the Technology-to-Performance chain (TPC) model, an interviewer-administered cross-sectional survey was conducted among 250 smallholder farmers in Uganda. Descriptive statistics were generated in SPSS to characterise the respondents and partial least squares structural equation modelling (PLS-SEM) was conducted in SmartPLS 4 to predict the hypothesised relationships. The results show that both perceived task Technology fit (PTTF) and current mobile phone use predict PPI, with PTTF being a stronger predictor of PPI. PTTF is best explained by task characteristics, while respondents' current mobile phone use is strongly influenced by social norm. This study advances the TPC model and contributes to understanding the factors and strategies that can be leveraged to enhance perceived performance impacts of mobile phones among smallholders. They are useful for researchers, policy makers, mobile phone application developers and agricultural practitioners.

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1. Introduction

New opportunities that could help achieve global sustainable development goals are presented by the growth of information and communication technologies (ICTs), such as mobile phone technologies in poor nations (Abebe, 2023; Namyenya et al., 2021). The annual increase in publications addressing various aspects of mobile phone adoption among farmers proves that mobile phone technologies have grown in relevance and attracted a great deal of interest among researchers and practitioners (Aparo et al., 2022). Whether it is to facilitate financial inclusion, ease access to information and markets, aid communication, or simplify reporting and farm management (Chiumia et al., 2020; Mdoda & Mdiya, 2022; Okello et al., 2020), there is a widespread acceptance among policy-makers and academicians that mobile phones constitute one of the main delivery channels for social, economic and human development in most developing economies (Duncombe, 2011; Mugwisi et al., 2014; Vimalkumar et al., 2020). The information systems (IS) literature on the benefits and adoption of mobile phone technologies (MPTs) in the agricultural sector is well established;

CONTACT Nathaline Onek Aparo nathalineonek.aparo@gmail.com Division of Agri-Food Marketing and Chain Management, Department of Agricultural Economics, Ghent University, Coupure Links 653, 9000 Ghent, Belgium.
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however, knowledge about the decisions of smallholder farmers to use this information technology remains scarce (Asravor et al., 2021), especially in developing countries (Dwivedi et al., 2017). Evidence from past studies points to farmers' continued reluctance to use MPTs to perform or coordinate farming tasks despite reportedly high mobile phone ownership rates (Landmann et al., 2020; Mutuma et al., 2023) and widespread publicity (Singh & Kapoor, 2023). The large disadoption or drop in MPT use has raised questions among researchers and practitioners alike (Michels et al., 2019). In an effort to address some of these questions and unravel the adoption paradox (Osang, 2015), the extant literature on mobile phone adoption in a farming context has examined the variables that affect behavioral intention to adopt (Kabbiri et al., 2018; Molina-Maturano et al., 2021), actual adoption, willingness to pay (Abebe, 2023; Bonke, 2018), willingness to adopt (Diaz et al., 2021), or other indicators of adoption such as attitude (Abdullahi et al., 2021), use frequency (Filippini et al., 2020), mobile phone ownership (Krell et al., 2020) and discontinuation of usage (Kenny & Regan, 2021). Although mobile phones hold great promise for addressing the needs of smallholder farmers, their perceived performance impacts (PPI) remain less explored in current studies on the adoption of mobile phones among smallholders. However, scientific evidence suggests that perceptions of performance impacts are essential for farmers to continue using MPTs (Aparo et al., 2022), and for digital technology use as a whole (Omotayo & Haliru, 2020). Previous studies have primarily investigated smallholders' decisions to adopt MPTs from a utilization standpoint. However, in a technology dissemination context, adoption or usage should theoretically converge with the concept of task-technology fit (TTF) or the extent to which a technology helps someone carry out their range of tasks (Goodhue & Thompson, 1995; Staples & Seddon, 2004). Perceived mismatch between technology, tasks, and needs contributes to delayed adoption and lack of sustainability in the use of digital technologies in agriculture (Makinde et al., 2022; Mushi et al., 2023; Tse et al., 2018). Recent information systems (IS) literature provides strong empirical justification for extending the current adoption theories with a construct that considers perceived task-technology fit (PTTF) as it relates to MPTs (El-Masri et al., 2023).

The vast impact literature reports on the impacts of mobile phone use in farming (e.g. Aker et al., 2016; Jin & Li, 2022; Martin & Abbott, 2011; Quandt et al., 2020), but does not discuss their perceived performance impacts or the factors that influence them. Further research is needed to determine the salient factors that influence the perceived performance impacts (PPI) of mobile phone use, and how this relates to the PTTF concept. Considering the above, this study aimed to assess the drivers of the perceived performance impacts of mobile phone use among smallholder farmers in Uganda. Specifically, the influence of PTTF and present usage (U) on PPI was examined. Accordingly, the study answers the following four questions: (1) What are the factors associated with the PTTF of mobile phone use among smallholders? (2) What factors influence the current mobile phone use (U) among smallholders? (3) What influence do PTTF, and U have on PPI? (4) What are the influences of sociodemographic variables on the TPC model constructs?

This study subscribes to a line of reasoning that suggests that people's usage of technology is influenced by both task requirements and the degree to which the technology is suitable for them (Goodhue & Thompson, 1995). According to Njenga et al. (2016), MPTs may only be accepted and result in good performance outcomes if they offer features and support tailored to the needs of the user and work at hand. Therefore, our underlying assumption that PPI might be linked to both current use and perceived fit between mobile phone characteristics and agricultural tasks characteristics is supported by earlier studies on technology adoption in non-farmer settings (Dishaw & Strong, 1999). To this end, the Technology to Performance Chain (TPC) model adopted in this paper incorporates the task-fit lens, in addition to the utilization lens so frequently adopted in other theories of behavior and attitudes.

In the sections that follow, the motivations for, and contributions of this study are presented based on a review of the extant literature on farmers' adoption of MPTs and other information technologies. Next, the conceptual model, along with proposed hypotheses are provided, then the methodology is described, and the results are presented. Discussion and conclusions are provided at the end of the paper.

1.1. Motivations and contributions of the study

Numerous theoretical models have been proposed and utilized to investigate information system (IS) and Information Technology (IT) adoption and usage over the past few decades (Tam et al., 2018; Zamani et al., 2022). In particular, the fit and utilization perspectives have been employed separately in prior studies to better understand how technology is accepted

(Cai et al., 2023). Although both viewpoints are important for understanding the adoption and use of mobile phone technologies, neither viewpoint is sufficient on its own. According to Yi et al. (2016), to address the issues and shortcomings pertinent to both viewpoints, it is necessary to prioritize a comprehensive model that links perceived performance impacts to both PTTF and utilization. Therefore, the theoretical framework for this study is based on the Technology-To-Performance Chain model which combines these two essential vantage points (Goodhue & Thompson, 1995). Although the TPC model was initially created to predict organizational performance and the use of information systems (Aljukhadar et al., 2014), researchers assert that the PTTF is correlated with users' views, including perceived usefulness (PU) and perceived ease of use (PEOU) of new technologies (Mathieson & Keil, 1998). Since the inception of the model, researchers have extensively used it to investigate the relationship between PTTF, use, and performance. However, its operationalization has varied greatly. For example, in different contexts, the model has been used to identify the links between TTF and system use (Klopping & McKinney, 2004), or behavioral intention (Huang et al., 2013). Some studies ignore the relationship between PTTF and perceived impacts (Junglas et al., 2008) whereas others do not link PTTF to either system use or performance. Instead, they modelled PTTF to affect behavioral intention only (Lin & Wang, 2012; Yuan et al., 2010). More recently, the TPC model has undergone extensions with constructs of other theories, particularly the Technology Acceptance Model (TAM) (Rai & Selnes, 2019; Wu & Chen, 2017). Using the extended TPC, previous research has examined how different technologies correlate with their intended uses, including mobile business applications in Japan, the USA, and Korea (Gebauer et al., 2004), mobile instant messaging and students' academic performance in South Africa (Bere, 2018; Lee et al., 2005), decision-making tools (Erskine et al., 2019; Goodhue, 1998), utilization of social networking sites in China (Lu & Yang, 2014), mobile field computing in police (Ioimo & Aronson, 2004), computed tomography patient transfer between hospitals in China (Chen et al., 2015), and adolescents' access to health information in the US (Sheehan et al., 2012). The extended TPC model has also been applied to MPTs (Gebauer & Shaw, 2014), albeit much of the work has targeted the health, business, law enforcement and government sectors in regions outside sub-Saharan Africa according to two recent reviews (Jeyaraj, 2022; Spies et al., 2020). Despite a careful examination of the research pertaining to mobile phone adoption, the authors did not find any study that examined factors that influence the perceived performance impacts of mobile phones or assessed mobile phone adoption among farmers using the TPC model. Additionally, no study has examined smallholders' adoption of mobile phones from the PTTF perspective. To address these gaps and to contribute to current mobile phone adoption and impact literature, this study applied the TPC model to examine the factors that determine perceived performance impacts related to agricultural mobile phone use among smallholder farmers.

Theoretically, this paper is novel in its quest to advance the TPC model and address the neglect of the 'fit focus', particularly the importance of perceived task-technology fit in mobile phone adoption research, especially among a less studied group, smallholder farmers. Most studies that examine mobile phone adoption or post-adoption behavior either lack theoretical underpinnings or frequently apply 'common' theories, such as TAM and Unified Theory of Acceptance and Use of Technology (UTAUT) (El-Masri et al., 2023; Niknejad et al., 2020). This study addresses both limitations by applying a comprehensive research model that combines the fit and use perspectives and aims to both synthesize current research on mobile phone adoption and guide future research on the drivers of perceived performance impacts and continued use of mobile phone technologies among smallholder farmers. The study also extends the scope of research on mobile phone technology adoption in Sub-Saharan Africa, a context characterized by large numbers of smallholder farmers and exponential growth in the use of mobile phone technology (Ahikiriza et al., 2022), yet remains largely under studied (Jeyaraj, 2022). Establishing the drivers of perceived performance impacts of mobile phone use among smallholders is essential for researchers, policymakers, agricultural practitioners, and digital technology application developers to improve the performance impacts of mobile phones and consequently build strategies to deliver services effectively and efficiently through the technology to farmers.

1.2. Hypotheses development

This study examined the connections between smallholders' assessments of PTTF, U, and PPI. The core hypothesis of the study is that PPI is driven by both PTTF and the current utilization of mobile phones, which is consistent with well-known IS research (Dishaw & Strong, 1998; 1999; Goodhue & Thompson, 1995). The PTTF evaluates a technology's perceived ability to support and enhance task performance while considering factors such as compatibility, functionality, and usability (Goodhue, 1998). This supports the tenet that PTTF results from the interaction of technology characteristics (TEC) and task characteristics (TAC) (Franque et al., 2022; Marikyan & Papagiannidis, 2022). Consequently, technology that has features that are appropriate for the task at hand is more likely to be adopted and used successfully than technology that does not (Ratna et al., 2018). For instance, effective coordination and communication between smallholders and buyers are essential for marketing tasks. Therefore, mobile phones and other technologies with real-time communication and collaboration capabilities would be appropriate for such tasks. However, a technology with a user-friendly interface and advanced data input capabilities may be even more appropriate if a task is highly structured and requires exact data entry. In this study, technology characteristics are defined as aspects of mobile phones, such as portability, text and application-based instant messaging, video and audio capabilities, convenience, usefulness, and ease of use, which facilitate smallholder farmers performing particular agricultural tasks. Consideration of the task features that can lead users to rely more heavily on information technology components becomes valuable when introducing technology, such as mobile phones, to a specific user group. In a farming context, for example, the need to (1) seek market and price information; (2) consult agricultural experts, extension agents, other farmers, and traders; (3) maintain farm management records; (4) obtain up-to-date weather data; and (5) access farm inputs might cause farmers to rely more on the accessibility of mobile phones, their relative ease of use, and their ability to communicate reliably and promptly via data, voice, and SMS (Kabbiri et al., 2018). Thus, we hypothesize as follows:

> H1: Task characteristic is positively associated with perceived task-technology fit.

> H2a: Mobile phone characteristic is positively associated with perceived task-technology fit.

> H2b: Mobile phone characteristic is positively associated with perceived ease of use.

In contrast to earlier research that modeled the direct influence of PTTF on utilization (El-Masri et al., 2023), this study adopts the recommendation of McGill and Klobas (2009) to explore the impact of PTTF on mobile phone utilization through its antecedents. Therefore, social norm (SN), PU, and PEOU are considered antecedents of current mobile phone use in this research. Social norms has attracted a lot of interest among social science researchers who posit that human behavior is driven by some informal rules (Angerer et al., 2024). Therefore, smallholders' expectations of what other people do and what other people approve of doing represent social norms (Dimant, 2023; UNICEF, 2021). Extant research shows that social networks, including friends, family, peers and group can influence an individual's behavior through the day to day interactions (Filippini et al., 2020; Tscherning & Mathiassen, 2010). In other words, farmers' usage and perceptions regarding performance impacts of mobile phones may be influenced by the behavior, expectations and approval of people they consider important (Ajzen, 1991). The premise underlying the TPC model's linkages between PTTF and TAM constructs (i.e. PEOU and PU) is that PTTF substantially influences how people perceive the usefulness, simplicity, and usability of a technology (Larsen et al., 2009; Staples & Seddon, 2004). As perceived fit (PTTF) improves, it is anticipated that users' opinions on mobile phone usefulness and usability will increase. Accordingly, the following hypotheses was proposed:

> H3a: Perceived usefulness is positively associated with perceived task-technology fit.

> H3b: Perceived ease of use is positively associated with perceived task-technology fit.

The association between PU, PEOU, SN, and utilization is strongly supported by studies applying behavioral and attitudinal theories, including TAM, UTAUT, and TRA (e.g. Davis, 1989; Okoroji et al., 2021; Venkatesh & Davis, 2000). Although earlier studies mostly examined the influence of these factors on future utilization, this study assessed their impact on present mobile phone use. This is essential for providing insight into the elements that may influence smallholders' long-term adoption or rejection of mobile phone technologies. Thus, this study postulates that:

> H4a: Perceived ease of use is positively associated with current mobile phone utilization among smallholders.

> H4b: Perceived usefulness is positively associated with current mobile phone utilization among smallholders.

> H4c: Social norm is positively associated with current mobile phone utilization among smallholders.

The TPC model adopted in this study posits that perceived performance impacts (i.e. *users' subjective assessment of the extent to which a particular technology will positively impact their performance in completing tasks or achieving goals*) will be positively predicted by both current use and PTTF (Jeyaraj, 2022), PTTF will do so more significantly (D'Ambra et al., 2013; Harrati et al., 2017). While identifying and quantifying the performance influenced by mobile phones may be challenging, users' perceptions can be used to estimate the performance impacts, according to Yi et al. (2016). Consistent with this reasoning, this study examined the factors that influence perceived performance impacts (PPI) (i.e. *perceptions of smallholders*) rather than actual performance impacts. Studies have shown that user expectations and beliefs about how a technology would enhance their productivity, efficiency, accuracy, and overall task outcome determine their perceptions of performance impacts (Ratna et al., 2020). Therefore, users are more motivated and eager to accept and use a technology when they are aware of its performance benefits (Abu-Khalaf & Hmidat, 2020; McDonald et al., 2015). Performance impacts should also increase if the technology satisfies the user's needs (i.e. their tasks) and capabilities, because it will be easier to complete the necessary task. Previous studies have found support for a positive correlation between PTTF and performance (Dishaw & Strong, 1999; Staples & Seddon, 2004). Thus, we postulate that:

H5a: Perceived task-technology fit is positively associated with perceived performance impact.

Before gains in performance and PTTF can be realized, technology must be utilized (Trice & Treacy, 1986). Performance: the successful completion of a task or set of tasks can also be impacted by the utilization of a technology or the lack thereof. Increased usage should improve performance if the technology is well-designed (Ratna et al., 2020). Because gains in efficiency and effectiveness are lost when a technology is not used, its non-use should have a negative influence on potential performance (Staples & Seddon, 2004). Therefore, the hypothesis below was tested:

H5b: Smallholders' current use of mobile phones is positively associated with perceived performance impacts.

Finally, the assumption of homogeneity seems impractical in many real-life circumstances because people, groups, and organizations are likely to differ in their views and assessments of latent constructs (Becker et al., 2022; Schlägel & Sarstedt, 2016). This is particularly true in the context of socioeconomic research, such as farmer studies, where variations in factors linked to diverse subpopulations, such as culture, sex, education, and nationality, are routinely explored (Ting et al., 2019). Sarstedt et al. (2011) recommended consideration of population variability when utilizing aggregate data to minimize significantly skewed conclusions. To this end, group comparisons have been used extensively in recent studies to uncover variations in population subgroups that are not readily apparent when studying the total sample (Cheah et al., 2023; Matthews, 2017). In particular, studies on the adoption of mobile phones have revealed that socio-demographic factors, such as age, sex, mobile phone ownership, farm size, income, use frequency and educational attainment, have an impact on people's perceptions of the connections between latent constructs in theoretical models (Elena-Bucea et al., 2021; Ramírez-Correa et al., 2015). Moreover, as noted by Gupta and Jain (2015), each section of a population has its own needs and issues that can result in variations in perceptions and factors that influence the adoption of technology and performance outcomes. When the distinctions between the various segments are acknowledged, the adoption process, factors influencing present use, and attitudes of smallholders in Uganda become more apparent. This would assist policymakers, application developers, and agricultural extension programs in developing effective promotional tactics and achieving larger advantages. Therefore, the following hypotheses are formulated and tested.

H6a: The hypothesized structural model relationships differ across sociodemographic groups.

H6b: Perceived performance impact differs across sociodemographic groups.

The conceptual model and hypotheses evaluated in this study are depicted in Figure 1.

2. Materials and methods

2.1. Questionnaire design

To assess the determinants of PPI for mobile phone use among smallholders, a face-to-face questionnaire survey was conducted. The questionnaire consisted of two sections. The first section asked for general information about farmers' sociodemographic characteristics, including sex, education, age, farm size, mobile

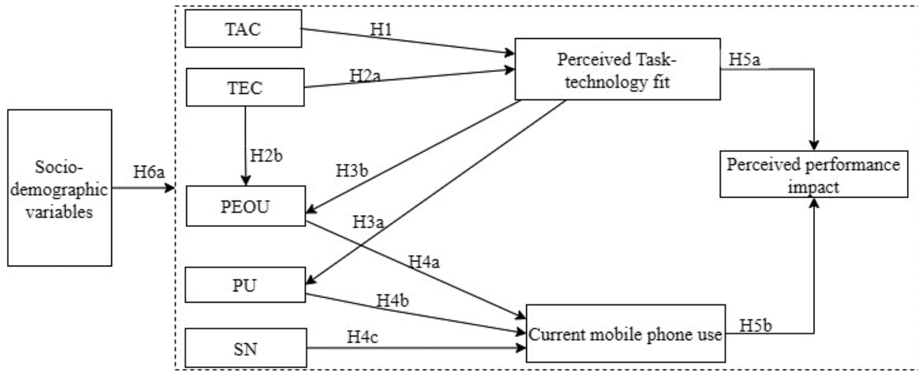

Figure 1. Conceptual Model for assessing perceived performance impacts of mobile phone use among smallholders in Uganda.
Source: (Aljukhadar et al., 2014; Dishaw & Strong, 1999; Goodhue & Thompson, 1995). TAC, Task-characteristics; TEC, Technology characteristics; PU, perceived usefulness; PEOU, Perceived ease of use; SN, social norm.

phone ownership and use frequency, and income level. Sex and mobile phone ownership were measured as binary categorical variables. Smallholders' mobile phone use frequency was measured using a 5-point Likert scale with 1 denoting 'Never' and 5 representing 'Always.' In the second section, the respondents were asked to indicate their level of agreement to each of the TPC model constructs i.e. PTTF, TAC, TEC, PEOU, PU, U, SN and PPI. The measurement items for each construct were adopted from previous studies and have been shown to be valid and reliable (Bere, 2018; Larsen et al., 2009; McGill & Klobas, 2009). These items were further refined during a pilot test with a sample of thirty-five farmers from the region. After the pilot test, the wordings of the items under PTTF, TAC, TEC and PPI were modified for easy comprehension and to fit the study parameters better. *As recommended by* Hair et al. (2017b), *each TPC construct is based on three to five measurement* items. Accordingly mobile phone characteristics also known as technology characteristics (TEC) included five statements (e.g. Mobile phone's *SMS and application-based texting, audios and video* capabilities make communication and information search more convenient and flexible; Mobile phones offer an *active and convenient* way to search for market and price information and Using mobile phones facilitates *direct* interaction with agro-input dealers). Task characteristics (TAC) was also measured by five items including 'I need to actively and conveniently *search for market and price information*,' '*Maintaining and managing my farm records* is an important task that I need to perform,' and 'I often need to *consult agricultural experts, extensions and my peers*.' Perceived task-technology fit (PTTF) had five items (e.g. Within my agricultural practice, I would like to handle my marketing tasks including searching for market and price information in an active and convenient way; Within my agriculture practice, I would like to directly communicate to buyers, Agri-input dealers, my peers and agricultural experts; Within my agricultural practice, I would like to address problems on the farm by seeking agricultural extension advice and solutions in a timely way). Perceived ease of use (PEOU) was measured by five items including 'It is difficult to communicate with people using a mobile phone,' and 'It is generally easy for me to use a mobile phone.' Perceived usefulness (PU) included five items e.g. 'Using a mobile phone will make it easy to acquire up-to-date market and price information,' and 'Using a mobile phone will improve my farm record management and resultantly general productivity.' Social Norms had four items including 'I will make agricultural consultations using mobile phones because the agricultural extension workers in my sub-county approve of it and use it themselves,' and 'It is not the norm for people in my social network to use mobile phones for agricultural-related purposes.' Utilization was measured using three items (e.g. 'I use mobile phones regularly to connect to agro-input dealers,' and 'I communicate with my peers and other people in my social network using mobile phones.' Perceived performance impacts was measured using five items (e.g. 'Mobile phones could improve my farm record management and enhances productivity,' and 'I am able to respond to the request of my buyers promptly with my mobile phones, thus avoiding delays.' Respondents rated each item on a 5-point Likert scale, with '1' representing strongly disagree and '5' representing strongly agree. The 5-point Likert scale was chosen because it is the one that researchers most frequently recommend to minimize respondent frustration, boost response rate and quality, and make it relatively easy for interviewers to read the full list of scale descriptions (Babakus & Mangold, 1992; Dawes, 2008; Zamhari & Abdullah, 2014). The detail of the constructs and measurement items is provided in supplementary Table 1.

2.2. Data collection process

Introductory letters to conduct the study were obtained from Gulu University, Gulu District Department of Agriculture, and local authorities in the study locations before the questionnaires were distributed. Responses were collected from smallholders in six sub-counties, namely Awach, Palaro, Paicho, Patiko, Unyama, and Bungatira, in the Gulu district of Northern Uganda. The Northern region was selected because, according to the 2019/2020 Uganda Bureau of Statistics agricultural census, over 900,000 (22%) of all farm households nationwide were located in the Northern region (UBOS, 2021). Although smallholders who participated in the survey were randomly selected, only adults who owned or had access to a mobile phone, had been farming in the 12 months prior to the survey and provided both informed written and oral consent to participate in the study were eligible to participate. Trained and qualified research assistants distributed the questionnaires to respondents using smartphones that were pre-installed with the Mwater application (Feighery et al., 2015; Yoo & Lenczewski, 2022). The mWater app is a free and open-source data collection and visualization platform that works with both Android and iOS systems. Data screening was performed to exclude invalid surveys from the 250 completed questionnaires. Because there were no duplicate or missing responses, all responses were considered during the data analysis.

2.3. Statistical analyses

First, raw data were exported from the mwater application (Xls. format) to the Statistical Package for Social Sciences (SPSS, version 28) software, cleaned and all negatively worded items in the different constructs were reverse-coded. Descriptive statistics in the form of frequencies, means, and standard deviations were generated to characterize the respondents.

Subsequently, the cleaned data were exported to SPSS (Xls. format) and imported into SmartPLS 4. Three-stage partial least squares structural equation modelling (PLS-SEM) was conducted to assess the predictive correlations between the constructs in terms of PTTF, PPI, and use, and to test the proposed hypotheses (Hair et al., 2019). The choice of PLS-SEM over covariance-based (CB-SEM) structural equation modelling was justified by its greater statistical power and better convergence behavior despite model complexity (Henseler, 2010; Henseler et al., 2016a). Using the central limit theorem, the PLS-SEM algorithm enables the automatic transformation of non-normal data (Hair et al., 2014). Therefore, researchers recommend PLS-SEM as rigorous for the analysis of non-normal data, which is typical for social science data, as it often does not follow a multivariate normal distribution. This study's sample size of 250 exceeded PLS-SEM 's threshold requirement of 205 (Hair et al., 2013).

The first two steps of the PLS-SEM analysis comprised the creation and assessment of the measurement and structural models. A single metric is not sufficient to assess model fit and quality (Liu et al., 2013; Park & del Pobil, 2013). Therefore, the assessment of both the measurement and structural models relies on multiple indices (Hair et al., 2019). Thus, the measurement model was evaluated using three parameters: convergent validity, discriminant validity, and construct reliability. The internal consistency reliability for each construct was assessed using Cronbach's alpha (Cronbach, 1951) and composite reliability (Henseler et al., 2016a). Convergent validity was estimated using average variance extracted (AVE) (Hair et al., 2014). The extent to which a construct differs from other constructs, also known as discriminant validity (Rasoolimanesh, 2022), was estimated using the heterotrait-monotrait (HTMT) criterion (Henseler et al., 2015). This criterion measures the ratio of correlations within a trait to those between traits (Hair, Black, et al., 2019).

To evaluate the proposed relationships between constructs, the structural model was assessed using indices, such as Value Inflation Factors (VIF), predictive relevance (Q^2), f^2 effect sizes, predictive accuracy (adjusted R^2), Standardized Root Mean Square Residual (SRMR), and path coefficients (Hair et al., 2017; Stone, 1974). The study used a non-parametric bootstrapping approach using the proposed 5000 samples (Hair et al., 2017b) to determine the significance of the hypotheses, and the Q^2 of each endogenous latent factor was determined using PLSpredict procedure (Chin & Todd, 1995; Tenenhaus et al., 2005). The constructs of the internal model were also examined for multicollinearity, the presence of which could cause problems in interpreting the PLS-SEM results.

The final phase of the study examined whether there were notable variations in the relationships among population subgroups. To do this, Henseler's multi-group analysis (PLS-MGA) was conducted (Hair et al., 2019). The three-step MICOM procedure was followed to check for configural invariance, compositional invariance and equality of composite mean values with respect to the different groups (Sánchez-Prieto et al., 2017). While the variables mobile phone ownership, education and sex satisfied the requirements for all stages of the MICOM procedure, the estimates for the age groups, household income levels and agricultural phone use frequency did not satisfy the requirement of configural invariance which is the first step in the MICOM procedure. Since it is recommended that research should move on to the next step only if the analysis from the preceding step confirms measurement invariance (Henseler et al., 2016b), these three variables (age, income and use frequency) were dropped from the PLS-MGA. Thus, for the PLS-MGA, the total sample was divided into three subgroups according to sex, education, and mobile phone ownership. To identify if there exists differences in perceived performance impacts across various social demographic subgroups, Kruskal-Wallis test was performed.

3. Results

3.1. Smallholders' socio-demographic characteristics

The smallholders included in this study were, on average, 39 years old, and had 17 years of farming experience. The farmers owned and farmed an average of 4.01 acres. The average household size and income were six persons and USD 570, respectively. More than half of the respondents were educated while 30% had received no formal education. Of the 250 smallholders interviewed, 68% were female and 63% owned mobile phones. Among the 63% of farmers who had mobile phones, only 4% owned smartphones. Most smallholders had owned their mobile phones for at least five years. Interestingly, only a few smallholders (9%) reported using mobile phones daily for agronomic purposes. The majority said that they rarely (33%) or never (26%) used their mobile phones for agricultural tasks. The results are provided in Table 1.

Table 1. Respondent's sociodemographic characteristics ($N = 250$)

Respondent characteristics	Mean	Standard deviation
Age	39.03	13.86
Household income (UGX.)	2,109,376	2,333,859
Household size	6.29	2.53
Farm size in acres	4.01	2.90
Farming experience (years)	17.62	14.21
Phone ownership duration (years)	5.18	5.004
Education	N	**Frequency (%)**
Formal education	175	70
No formal education	75	30
Gender		
Male	80	32
Female	170	68
Mobile phone ownership		
Owners	158	63
Non-owners	92	37

N, Number of respondents in each category, Formal education; Primary (48%), Secondary (17%), Tertiary (4%) and University (1%).

3.2. Relationship between the model constructs

This section assesses each stage of the SEM analysis, including the estimates of the measurement and structural models, before presenting the results of the proposed relationships in the model. Validity and reliability were evaluated for the reflective measurement model (Table 2). Composite reliability and Cronbach's alpha were above the recommended value of 0.7, demonstrating acceptable construct reliability and internal consistency of the items measuring the latent constructs (Cronbach, 1951; Henseler et al., 2016a). Along with the composite reliability values, the AVE for individual constructs also exceeded the threshold of 0.5 for multivariate constructs (Hair et al., 2019), confirming convergent validity.

Furthermore, none of the HTMT values (Table 3) exceeded the recommended maximum value of 0.85, establishing discriminant validity (Hair et al., 2017a).

The assessment of the structural model fit revealed acceptable values of the metrics (Table 4), indicating an adequate fit. The SRMR value of 0.063 is less than the 0.08 criterion suggested by Hu and Bentler (1998) and all VIF values are below 5, indicating that there

Table 2. Construct reliability and validity of the measurement model

Construct	A	(rho_A)	(rho_c)	AVE
PEOU	0.9	0.9	0.9	0.7
PPI	0.9	0.9	0.9	0.7
PU	0.8	0.8	0.8	0.6
SI	0.7	0.7	0.7	0.5
TAC	0.8	0.9	0.8	0.6
TEC	0.6	0.8	0.7	0.5
PTTF	0.7	0.7	0.7	0.5
U	0.8	0.8	0.8	0.6

TAC, task characteristics; TEC, technology characteristics; PPI, perceived performance impact; PTTF, Perceived Task-Technology Fit; U, current Utilization of Mobile phones; PEOU, perceived ease of use; PU, perceived usefulness; SN, social norm, and AVE = Average variance extracted; both rho_A and rho_c denote composite reliability; and α = Cronbach's alpha.

Table 3. Heterotrait-monotrait criterion assessment of discriminant validity of constructs

	PEOU	PPI	PU	SI	TAC	TEC	PTTF	U
PPI	**0.427**							
PU	0.31	**0.393**						
SN	0.44	0.23	**0.074**					
TACS	0.411	0.327	0.159	**0.561**				
TEC	0.475	0.304	0.147	0.787	**0.767**			
PTTF	0.61	0.633	0.502	0.112	0.399	**0.237**		
U	0.398	0.17	0.11	0.71	0.625	0.719	**0.151**	

TAC, task characteristics; TEC, technology characteristics; PPI, perceived performance impact; PTTF, Perceived Task-Technology Fit; U, current Utilization of Mobile phones; PU, perceived usefulness; SN, social norm.

Table 4. Indicators of model fit for the structural model

Latent variable	Adj. R^2	Q^2	VIF	SRMR
PTTF	0.157	0.076	2.165	
PEOU	0.474	0.085	1.612	
PU	0.250	0.005	1.435	
U	0.509	0.036	1.414	
PPI	0.406	0.059	1.023	
Goodness-of-fit measure				0.063

PPI, perceived performance impact; PTTF, Perceived Task-Technology Fit; U, current utilization of mobile phones; PEOU, perceived ease of use; PU, perceived usefulness; SN, Social norm, Q^2 values are presented for endogenous variables only. $Q2>0$ is indicative of predictive relevance and VIF, Value Inflation Factor. R^2 values of 0.25, 0.50, and 0.75 signify weak, moderate, and substantial predictive accuracy of the exogenous factors on the endogenous variables (Hair et al., 2011; Henseler et al., 2009); SRMR, Standardized Root Mean Square Residual.

are no critical values for multicollinearity in the model (Hair et al., 2013). Furthermore, all Q^2 values were higher than zero, indicating that the model had predictive relevance (Stone, 1974). The model explained 40.6% of the variance in the PPI.

The PPI of mobile phone use among smallholders was significantly positively influenced by PTTF ($\beta=0.626$; $P<0.001$) and U ($\beta=0.147$; $P<0.001$). PTTF also significantly and positively influenced the PEOU ($\beta=0.525$, $P<0.001$) and PU ($\beta=0.497$, $P<0.001$) of mobile phones among smallholders. As predicted, the PTTF was significantly and positively influenced by TAC ($\beta=0.$ 0.468, $P<0.001$), and TEC ($\beta=0.074$, $P<0.001$), with the former having a greater effect. TEC also positively influenced PEOU ($\beta=0.333$, $P<0.001$). The only significant determinant of current mobile phone use among the smallholders was SN ($\beta=0.671$, $P<0.001$). Unexpectedly, no influence on current use was found for PU or PEOU. In general, the effect of the main determinants in our model is largest for PTTF, TAC, and SN. The results and the corresponding *p*-values and significance levels for each hypothesized relationship are shown in Table 5.

The PLS-MGA results (Table 6) demonstrate that there were variations in certain path coefficients between the groups. Although the influence of PEOU on current mobile phone use was not significant in the pooled sample, the multi-group analysis showed that the influence of PEOU on current use was positive and significant among female and educated farmers. PEOU and PU were positively and significantly influenced by PTTF among women. The PLS-MGA results also revealed that among smallholders who possessed mobile phones and were educated, the effect of TAC on PTTF and U on PPI were positive and significant.

The Kruskal-Wallis test results revealed significant differences in perceived performance impact across sex, age groups, income levels, education, mobile phone ownership and agricultural phone use frequency. Accordingly, the results allude to the perceived performance impacts being higher for respondents who are male, middle aged (36–45 years old), own a mobile phone, with regular phone use, high income, and post-secondary education (Table 7).

4. Discussion

The extent of mobile phone technology use and its performance benefits are two of the most relevant outcomes of interest for information systems researchers (DeLone & McLean, 1992). This study assesses the determinants of PPI associated with mobile phone use among smallholder farmers in Uganda. Considering the findings, the TPC conceptual model examined is valid and offers practical insights into the factors that influence the PPI of mobile phone use among smallholders. A review of the statistical significance and potency of the individual paths, coupled with the amount of variance explained by the model (40.6%), revealed that the PTTF construct had the most explanatory ability. These outcomes are in line with earlier research findings that PTTF had greater explanatory power than usage (D'Ambra et al., 2013; Harrati et al., 2017; Ratna et al., 2018). The findings suggest that smallholders who understand how mobile phone capabilities might help them complete a task are more likely to perceive their performance impact favorably. Thus, a high PTTF is necessary for mobile phone technology to be viewed as advantageous (Faqih & Jaradat, 2021). Smallholders' perceptions and willingness to utilize mobile phones may remain low if mobile

Table 5. Structural Model PLS path analysis results

Hypotheses	Path	Path coefficients	p Values	Significance levels	f^2	Outcomes
H5a	PTTF → PPI	0.626	0.000***	$p < .001$	0.65	Supported
H4c	SN → U	0.671	0.000***	$p < .001$	0.725	Supported
H3b	PTTF → PEOU	0.525	0.000***	$p < .001$	0.495	Supported
H1	TAC → PTTF	0.468	0.011**	$P < .05$	0.32	Supported
H3a	PTTF → PU	0.497	0.000***	$p < .001$	0.207	Supported
H2b	TEC → PEOU	0.338	0.000***	$p < .001$	0.205	Supported
H2a	TEC → PTTF	0.074	0.000***	$p < .001$	0.118	Supported
H5b	U → PPI	0.147	0.000***	$p < .001$	0.16	Supported
H4a	PEOU → U	0.092	0.391	$p > .05$	0.012	NS
H4b	PU → U	0.041	0.601	$p > .05$	0.03	NS

**$P < 0.05$; ***$P < 0.001$; f^2 is effect sizes; NS means the hypothesis was not supported.
TAC, task characteristics; TEC, technology characteristics; PPI, perceived performance impact; PTTF, Perceived Task-Technology Fit; U, current Utilization of Mobile phones; PEOU, perceived ease of use; PU, perceived usefulness; SN, social norm.

Table 6. PLS Multi-group analysis results

	Female ($N = 170$)			Male ($N = 80$)			
Relationships	Path coefficient	t Values	P values	Path coefficient	t Values	P values	Invariant
PEOU -> U	0.206	2.653	0.008**	0.101	0.774	0.439	No
PTTF -> PEOU	0.422	6.391	0.000***	0.1	1.036	0.3	No
PTTF -> PU	0.324	3.579	0.000***	0.244	1.456	0.146	No
	Non-owner ($N = 92$)			**Owner ($N = 158$)**			
TAC -> PTTF	0.213	1.418	0.156	0.384	3.069	0.002**	No
U -> PPI	−0.026	0.289	0.773	0.206	2.483	0.013**	No
	Educated ($N = 175$)			**Uneducated ($N = 75$)**			
PEOU -> U	0.217	2.657	0.008**	0.173	1.541	0.123	No
TAC -> PTTF	0.276	2.6	0.009**	0.253	1.612	0.107	No
U -> PPI	0.15	2.521	0.012**	−0.041	0.346	0.729	No

**$P < 0.05$, ***$P < 0.001$.
TAC, task characteristics; TEC, technology characteristics; PPI, perceived performance impact; PTTF, Perceived Task-Technology Fit; U, current utilization of mobile phones; PEOU, perceived ease of use; PU, perceived usefulness. All respondents with levels of education from primary school to university were considered educated, and those without formal education were considered not educated; non-owners refer to those who do not own mobile phones, while owners are those who own mobile phones.

Table 7. Group differences in perceived performance impacts

Variable	Group	N	Mean Rank	H-statistic	df	P-value
Gender	Male	80	166.36	37.924	1	0.000
	Female	170	106.27			
Age (Years)	18–25	42	117.65	18.533	4	0.001
	26–35	78	133.81			
	36–45	55	149.74			
	46–55	44	116.95			
	>55	31	84.35			
Education Level	No formal education	76	95.20	22.562	4	0.000
	Primary education	120	132.25			
	Secondary education	42	152.32			
	Other institutions	10	157.90			
	University	2	146.75			
Annual Income (Ugx)	< 500,000	65	81.74	53.466	5	0.000
	500,001-1,500,000	81	114.95			
	1,500,001–2,500,000	30	156.20			
	2,500,001–3,500,000	28	147.84			
	3,500,001–4,500,000	17	168.47			
	>4,500,000	29	174.53			
Phone ownership	Yes	157	143.08	25.179	1	0.000
	No	93	95.83			
Agric. Phone use	Never	66	121.14	40.119	4	0.000
	Rarely	83	99.68			
	Sometimes	57	126.76			
	Often	21	154.33			
	Always	23	201.72			

Ugx; Uganda shillings is the country's legal currency.

phone technology cannot enhance their (perceived) performance in performing the tasks they view as essential (Ahikiriza et al., 2022).

It is important to point out that model linkages were observed between hypotheses H2a (TEC -> PTTF), H2b (TEC -> PEOU), and H4a (PTTF -> PEOU), indicating that the PEOU of mobile phones is influenced by both TEC and PTTF. The results of earlier studies corroborate these conclusions (Dishaw & Strong, 1999; Faqih & Jaradat, 2021). It is anticipated that the cost of effort will decrease if mobile phone technology features (TEC) can assist smallholders in completing farming activities and objectives conveniently and swiftly (Gefen & Straub, 2005). According to Mwaseba et al. (2022), any effort to enhance agricultural development using mobile phone technologies might achieve better outcomes when founded on the core capabilities of mobile phones. Hypothesis (H4b) was confirmed because the PU of mobile phones increased by 49.7% when PTTF improved by one unit. Previous studies on other information systems have reported similar results (Faqih & Jaradat, 2021; Hsin Chang, 2010; Wan et al., 2020). These results were expected from a theoretical standpoint; perceptions of the usefulness and ease of use of mobile phone technologies increase with higher levels of perceived alignment (PTTF) (Venkatesh et al., 2003; Wan et al., 2020).

Strong support was found for the part of the TPC model linking TAC and TEC to the PTTF. This conforms with TTF theory and the existing literature (Goodhue & Thompson, 1995; Wang et al., 2020; 2021). The stronger influence of TAC on PTTF was particularly prominent, which is also consistent with previous studies (Dishaw & Strong, 1999; Faqih & Jaradat, 2021).

The only factor significantly associated with the current use of mobile phones by smallholders is SN, which includes extension workers, other farmers, family, and friends. This result suggests that smallholders are much more likely to use mobile phones when they encounter others who have a positive attitude towards their use for agricultural purposes. These findings are consistent with those of previous studies (Qanti et al., 2021; Yi et al., 2016), but not others (Beza et al., 2018; McGill & Klobas, 2009). Based on this study, the peer-to-peer extension approach can considerably enhance the current use of mobile phones (Ahikiriza et al., 2022).

The non-significant relationship between PEOU and PU with current mobile use in the pooled sample was much less expected. This contradicts the findings of previous studies, which found that usage and adoption intentions are influenced by these two factors (Kabbiri et al., 2018; Venkatesh et al., 2003). There might be different explanations for the inconsistency between this paper's findings and those of past studies. First, a possible explanation could be the difference in measurement methods. The present study assessed current mobile phone use while previous studies that found favorable impacts of PEOU and PU examined how they affected behavioral intention to use (i.e. future use). This could partially explain why other antecedents, such as SN, had a greater impact in this study. Second, these results could point to the possibility of reverse causation, wherein the respondents' present mobile phone use could also influence their perceptions on the ease of use and usefulness of mobile phone technology. Based on existing literature, the likelihood of reverse causation is very high in cross-sectional research such as ours, because it is challenging to determine the temporal sequence of cause and effect (Besser et al., 2021). Although our proposed model relationship between PEOU, PU, and current mobile phone use is strongly grounded in theory, growing empirical evidence points to the possibility of reverse causation relationships in TAM (Ishaq et al., 2021). This is because technology usage may offer further insights to users that shapes their perceptions of the technology's utility and ease of use (Sussman & Gifford, 2019). Future studies could attempt to address the issue of reverse causality through Randomized Control trials (Glass et al., 2013), quasi-experiments, including instrumental variable analysis (Besser et al., 2021), longitudinal study designs (Lamb et al., 2020), and sample restriction and stratification (Lamb et al., 2020).

The PLS-MGA results revealed substantial variations in the model linkages for sex, education, and mobile phone ownership. PEOU proved to be a significant factor for current use among females and educated smallholders only. This suggests that for women to accept and use mobile phones along with associated apps and services, their view of how simple they are to use must be favorable. Similarly, the paths (TAC → PTTF; U → PPI) are positive and significant for smallholder farmers who own mobile phones and are educated.

Based on the results of the Kruskal-Wallis test, differences in perceived performance impacts was found across age groups, sex, education, mobile phone ownership, use frequency and income levels. The higher perceived performance impacts among male respondents is consistent with the findings of previous studies that also reported more positive and higher perceived benefits related to agricultural mobile phone use among male farmers in Tanzania (Quandt et al., 2020) and Western Uganda (Masuki et al., 2010). In our study sample, more men than women reported owning mobile phones. This gap in mobile phone ownership could be attributed to the unequal access to resources and socio-cultural dynamics in which males can ably decide whether or not their wives or daughters can have mobile phones. Summers et al. (2020) found that men from the Maasai community in Northern Tanzania fully control women's access to or ownership of mobile phones. Thus, women might not fully realize the performance benefits that mobile phone use could deliver towards their agricultural production. The critical role that such gender disparities play in creating the 'digital haves' and 'have nots' should be considered when promoting the uptake of mobile phone technologies among smallholders. In line with a previous study (Issahaku et al., 2018) that reported that farmers who owned mobile phones had greater maize productivity than those who had no mobile phone or just borrowed one, this study also found that PPI is higher for mobile phone owners. Furthermore, the study results show that the younger farmers had significantly higher PPI than their older counterparts, which corroborates the findings of previous studies (Islam & Grönlund, 2012; Jain & Hundal, 2007). According to Asif et al. (2017), this result might be attributed to the fact that older farmers are typically more ingrained in their customs and traditional farming methods and knowledge; as a result, they use mobile phones considerably less when engaging in agriculturally related tasks. Likewise, compared to farmers with lower levels of education, the findings of this study show considerably higher perceived performance impacts among those with higher levels of education. This could be because education enhances peoples' learning and mobile phone use capabilities which makes it easier for them to use the technology for agricultural tasks including searching for information and consulting agricultural experts (DiMaggio & Cohen, 2021).

The higher perceived performance impacts associated with respondents who reported having higher income is supported by some previous studies. For instance, Khidir (2020) reported that farmers who cannot afford to buy mobile phones or maintain them due to their low-income status tend to use mobile phones less, thus experiencing much lower impacts. However, this contradicts the findings of Bayes (2001), who reported that the low-income earners in Bangladesh experienced a greater impact from mobile phones than the high-income earners. This is because they had a higher consumer surplus, measured in terms of transaction costs, compared to the high-income earners.

Consistent with an earlier study (Issahaku et al., 2018), higher perceived performance impacts was reported for respondents who used their mobile phones regularly compared to those who never or only occasionally used mobile phones for agricultural purposes.

4.1. Conclusions and recommendations

This paper had the overall objective of assessing the drivers of perceived performance impacts of mobile phone use among smallholders in Uganda. Generally, the results suggest that using the TPC model to examine the perceived impact of mobile phones on smallholders' task performance is a useful approach. The empirical, theoretical, and methodological contributions of this study to the current research are fourfold. First, it assesses the drivers of PPI, in contrast to previous research that only examined mobile phone adoption or use among smallholders. Changes in the agricultural and agribusiness sectors call for research that addresses smallholder farmers' perceptions of the performance impacts of mobile phone use, and the mechanisms by which they occur. Second, theoretically, this study uses the comprehensive TPC model that incorporates a PTTF perspective in addition to the use perspective, while offering explanations for the antecedents of perceived performance impacts and the interrelationships between them. In doing so, it enriches the extant mobile phone adoption and impact literature on smallholders, particularly in developing countries. This is crucial because the few extant studies on mobile phone uptake among smallholders have overlooked the importance of PTTF. Third, this study uses PLS-SEM, an advanced data analysis technique to estimate simultaneous correlations among factors that explain PPI of mobile phone use. Fourth, it goes beyond previous studies on mobile phone adoption by conducting a multigroup analysis based on smallholders' socio-demographic characteristics to examine group differences.

Despite the solid theoretical foundation and diverse contributions of this study, some limitations are worth mentioning. First, the study focused on Ugandan smallholders in the Northern region who owned or had access to mobile phones. This research needs to be extended to other sub-Saharan African regions with different or similar settings. Second, the study examined mobile phones and agricultural tasks from a general perspective and assessed perceived performance impacts (PPI). Moreover, we do not measure the influence of a specific mobile phone or agricultural characteristic that would influence PTTF. Rather we measure the effects of the construct as a whole. Further empirical insights could be gained by assessing and discerning the specific characteristics of mobile phones and agricultural tasks that are associated positively with PTTF. Future research might find it informative to test the TPC model with a specific agricultural mobile application using objective measures of performance impact. Third, although we found the influence of PTTF and current use on PPI, we did not investigate the influence of perceived performance impacts on future use and intention to use mobile phones for agricultural tasks. The existence of potential reverse-causal links in TAM, and the TPC model assessed here could be examined further in future studies. When assessing reverse causality in the TPC model, future researchers could consider a variety of individual and situational factors such as personal innovativeness, prior experience, use intensity, level of farm commercialization, and perceived enjoyment. Moreover, future empirical studies could apply longitudinal research designs, experiment designs such as randomized control designs and quasi experiments to establish the temporal order of outcomes and exposure. It may also be interesting for future research to differentiate between mandatory and voluntary use situations. The role of feedback in shaping PPI should also be explored in future studies.

This study sheds light on the mechanisms by which policymakers, researchers, application developers, extension agents, governments, and mobile service providers can promote mobile phone use and adoption for development among smallholders in Uganda by identifying how distinct groups of smallholder farmers value various relationships in the study model. It also provides service providers and policymakers with a comprehensive understanding of the determinants of PPI for effective strategic decisions at the user level.

One of the important conclusions of this study was that PTTF was the primary variable influencing PPI. The relevance of TAC in improving the PTTF is clearly supported by the current findings. Therefore, from a practical standpoint, we propose the following recommendations to stakeholders, including mobile phone application developers to improve PTTF: (a) include smallholders' TACs in the design phase of agricultural applications and mobile phones by consulting with colleagues and extension agents; (b) develop features that are easy to use to improve smallholders' assessment of TEC; (c) consider conducting pilot tests and trials to obtain feedback from smallholders and improve suitability features; (d) invest and engage in participatory technology research and innovation to co-create mobile phone solutions that meet the needs and aspirations of smallholders from diverse backgrounds; and (e) encourage collaboration between mobile phone application developers, agricultural experts, and farmer associations to share knowledge, experiences, and best practices.

In contrast to the greater percentages of smartphone owners in the previous studies (Ahikiriza et al., 2022; Tyagi et al., 2020), only 4% of smallholders in this study who owned mobile phones reported owning a smartphone. This indicates that the majority of these farmers may not yet be utilizing the entire range of features and services provided by farm-specific apps, and they may not have had the opportunity to utilize their mobile devices in ways that could help them perform better on their farms (Dehnen-Schmutz et al., 2016). Therefore, it could be strategic and informative for researchers, mobile phone application developers, and the government to investigate the reason for this low smartphone ownership rate. In addition, opportunities for partnerships between the government, mobile phone manufacturers, and service providers may be explored to ensure affordable and accessible devices for farmers, considering factors such as cost, durability, and ease of use. Such a partnership could offer subsidized smartphones or facilitate access through community centers or farmer cooperatives.

Given that most respondents in this study had low levels of education (30.4% had no formal education and 48% had primary education), comprehensive training programs tailored to different levels of education and technical skills should be provided by agricultural extension agents and government agricultural departments to improve the perceptions of usability among female smallholders. Additionally, the PLS-MGA results showed that PEOU positively influenced current mobile phone use among the farmers. Therefore, training could include the use of mobile phones, applications relevant to agricultural tasks, and digital literacy. In addition, peer-to-peer learning could help farmers gain insights from their peers, which would facilitate the use of mobile phones and thus improve their perceptions of the performance impact.

Authors' contributions

NOA: Conceptualization, data curation, investigation, initial analysis, formal analysis, methodology, writing-original draft, writing, review, and editing, funding acquisition; AOA: Conceptualization, investigation, methodology, initial analysis, review, and editing; WO: writing, review, and editing, supervision; HDS: Conceptualization, methodology, initial analysis, writing, review, and editing, supervision, funding acquisition.

Disclosure statement

The authors report there are no competing interests to declare.

About the authors

Nathaline Onek Aparo is an agricultural and rural development specialist. She holds a bachelor's degree in Agriculture from Gulu University, Uganda, and a joint degree of International Master of Science in Rural Development from Ghent University, Belgium, Pretoria University, South Africa, and the University of Pisa, Italy. Currently, she is pursuing her Ph.D. in the Department of Agricultural Economics and Marketing, Ghent University, and the Department of Agribusiness and Rural Development, Gulu University, Uganda. Her research work is focused on "leveraging mobile phone technology to improve smallholder agricultural productivity" and crosses the fields of behavioral Economics, Quantitative social research, Agricultural- and socio-economics.

Alice Onek Atimango is currently a PhD researcher at the Division of agrifood marketing and chain management, Department of agricultural economics, Ghent University. She holds an International Master of Science in Rural development of the same university and a Bachelor degree in agriculture from Gulu University in Uganda. Alice's research interest is in the fields of agricultural and social economics, agriculture and rural development and agri-food chain actors' behavior towards novel technologies in agriculture especially in the developing country context. Her current research work is focused on "gene editing in agriculture from a socioeconomic perspective".

Walter Odongo holds a Ph.D. in Applied biosciences (Agricultural economics) from Ghent University and a Master of Science in Agricultural and applied economics from Makerere University. He is a Senior Lecturer of Agricultural Economics at the Faculty of Agriculture and Environment, Gulu University, Uganda. Walter has 15 years of experience in training, capacity building, Agri-entrepreneurship development, and research in developing country contexts. His research interest is in the fields of agribusiness supply chain management, agricultural and rural development, agricultural economics, and community engagement. He has managed over ten projects and published over 20 scientific articles in international peer-reviewed journals.

Prof. Dr. Hans De Steur is currently an assistant professor in Quantitative Research Methods in socio-economics at the Division of Agri-food Marketing & Chain Management, Department of Agricultural Economics, Ghent University. He holds a master's degree in Sociology and in Economics and Business Administration. In 2011, he finished his Ph.D., which focused on the market potential of biofortification. His current research is situated in the field of agri-food marketing and socio-economic analysis, with a focus on consumer and stakeholder behavior and impact analysis of innovations and technologies. He was and is involved in various multidisciplinary research projects and has multiple publications in top-tier journals in different research domains.

Ethical approval statement

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

Geolocation information

The study was conducted in Gulu district, which is in Northern Uganda with GPS coordinates of 2° 46′ 20.6544″ N and 32° 17′ 17.0628″ E, and an elevation of 1114.036. The latitude of Gulu is 2.772404, and the longitude is 32.288073.

Informed consent statement

Both oral and written informed consent were provided by each respondent to participate in the survey.

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ORCID

Nathaline Onek Aparo http://orcid.org/0000-0003-2228-8386
Walter Odongo http://orcid.org/0000-0001-5811-5132
Hans De Steur http://orcid.org/0000-0003-1340-0882
Alice Onek Atimango http://orcid.org/0009-0006-9262-054X

Data availability statement

Data will be made available on request.

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