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The use of mobile phones and the heterogeneity of banana farmers in Rwanda

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Abstract

Information and communications technologies (ICTs) play a key role in improving agricultural production, enhancing socio-ecological resilience, and mitigating rural poverty. However, the use of ICTs for agricultural development among smallholder farmers, especially in the least developed countries, still lags behind. It is therefore critical to understand distinct attitudes among heterogeneous smallholder farmers that determine use of ICTs, such as mobile phones. Moreover, data-driven empirical studies on the use of mobile phones in smallholder settings are still scarce. We bridge this knowledge gap by evaluating the link between the use of mobile phones and various farming types of smallholder farmers in Rwanda. Using the principal component and cluster analysis, we analyzed 690 banana farming households across eight of the 10 major agro-ecological zones of Rwanda and developed a typology of banana farms. We identified three distinct farm types based on a combination of various farmer characteristics and farm operations and endowments, namely the beer banana, livestock-based, and the cooking banana farm types. These farm types clearly differ in terms of ownership and use of both basic and smart mobile devices. Farmers in the cooking banana farm type are far more likely to own and use smart mobile phones than in other types. Regression results further indicated that farm type, gender, and education have significant correlations with the perceived usefulness of mobile phones in agriculture. Major barriers to using ICT-based agricultural services were 1) low awareness of the existence of ICT services, 2) limited availability of ICT services, 3) lack of technical know-how, 4) relatively high prices of ICT devices, and 5) low levels of ICT literacy. This empirical study provides strategically important insights for the transition to digital agriculture in the context of smallholder farming systems.

Keywords ICTs · Mobile phone · Agricultural extension services · Small farmers · Banana production

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1 Introduction

Given the increasing demand to feed the world's rapidly growing population, ensuring sustainable agricultural development is crucial and indispensable. More so that the increase in crop yield does not rise at the same pace as the increase in food demand (Long et al. 2015). However, the effectiveness of several sectors is essential in ensuring sustainable agricultural development. For instance, communication, transfer of knowledge, and information exchange have played a significant role in the agricultural advancement from traditional to modern systems, and such advancements are expected to foster the agricultural transformation toward sustainable food systems (El Bilali & Allahyari, 2018; Zhang et al. 2016). Moreover, information and communication technologies (ICTs) can help boost efficiency and sustainable agricultural production by providing dynamic, reciprocal, and effective information exchange regarding agriculture-enabling innovations (El Bilali & Allahyari, 2018; Klerkx et al. 2019; Munthali et al. 2018; Zhang et al. 2016). With the term *innovation*, we refer to the successful combination of new technologies or tools (hardware), new knowledge or new modes of thinking (software), and the reordering of institutions and of organizations (orgware(Awan et al. 2021; Cheng et al. 2021; Hermans et al. 2017)).

ICTs today play an integral role directly or indirectly in agricultural and rural development by improving productivity, enhancing food security, and improving farmers' livelihood and general welfare (Sekabira & Qaim, 2017). ICTs can particularly improve communication and information access among actors along agri-food supply chains and other stakeholders, thus making development inclusive even for those who are located remotely. Smallholder farmers can benefit from ICTs, especially Internet infrastructure and mobile phones, which provide farmers with opportunities to easily access technological innovations, extension services, markets, and essential weather information (Debsu et al. 2016). From this perspective, it is argued that the use of mobile phone-based ICT platforms is also a potential way to reorganize and facilitate formal agricultural extension by delivering relevant, timely, and cost-effective information (Duncombe, 2016; McCampbell et al. 2018; Schut et al. 2016) and improve communication among farmers in the context of informal knowledge sharing networks (Vouters, 2017).

Although the literature presents a wide range of benefits of using mobile phones in agriculture, they do not guarantee the adoption of mobile-based technologies among farmers, particularly in smallholder farming systems, which still dominate in underdeveloped and developing countries. Failure to take into account the heterogeneity of farmers, especially smallholder farmers, has been identified as one of the potential barriers to innovation adoption (Coe et al. 2019; Hammond et al. 2017). Various studies in Sub-Saharan Africa have exposed high levels of variability among smallholder farmers in many characteristics, such as cropping, farm size, soil fertility, livestock assets, education, labor availability, and sociocultural traits (Bidogeza et al. 2009; Kansiime et al. 2018; Nabahungu & Visser, 2011; Tittonell et al. 2005). This variability results in diverging priorities that correspond to various behaviors concerning innovation adoption (Nabahungu, 2012; Tittonell et al. 2007).

Therefore, farm heterogeneity has a profound implication on farm households' efficiency and needed policy interventions. On one hand, the one-size-fits-all scaling approach, in which technologies are packed in one adoption package regardless of particular compatibility and risk aversion imposed by particular contexts of these diverse (heterogeneous) farms, is increasingly questioned (Cleary & Van Caenegem, 2017; McCampbell et al. 2018; Find Your Feet 2012). On the other hand, policies and measurements cannot be designed on an individual basis alone. This would be too time-consuming and costly.

This means that although heterogeneity among farmers needs to be considered, the common features among groups of farmers are also important in the design of communally feasible and targeted interventions. As a result, farm and farmer typologies have become increasingly popular. Typology construction is an efficient method to understand farmer diversity by delineating groups of farmers with common characteristics while considering general farmers' diversity and heterogeneity (Shukla et al. 2019). Farmer typology studies have been used to classify farm households based on socioeconomic characteristics to understand how they would change with the adoption of innovations based on their diverging priorities (Bidogeza et al. 2009; Hammond et al. 2017).

The most recent studies on the heterogeneity of farmers' adoption behaviors regarding the use of mobile phones have been mainly econometrics-based (i.e., regressions on farmers' characteristics; (Adegbidi et al. 2012; Islam & Grönlund, 2011; Tadesse & Bahiigwa, 2015). However, farmers' preferences have to be regarded in the context of the broader agricultural innovation systems (Martin-Collado et al. 2015). Instead of a narrow socioeconomic farmer typology, a broad typology in which farms and farmers are investigated together could be a starting point in predicting farmers' preferences regarding the adoption of mobile phones.

Therefore, to address this research gap, we take a broad farm and farmer typology approach to provide empirical evidence of links between mobile phone-based information delivery and farm diversity in the context of banana farmers in Rwanda. This study's contribution is twofold. First, we link farm heterogeneity with the use and perception of mobile phones in the context of smallholder farmers. Second, we provide a practical tool for projects intending to use mobile phones in agricultural production in a smallholder context. Specifically, we respond to the research question, "What combinations of farm/farmer types can be differentiated when it comes to the ownership and use of mobile devices?" In this case, we distinguish a farm typology (that contains various farm types based on farm characteristics, such as production system) and a farmer typology (that contains various farmer types based on farmers' characteristics, such as gender and age).

In the subsequent theoretical section, we start with a review of the farm heterogeneity perspective. In the next section, we explore the literature on the heterogeneity of farmers themselves and link them to the potential of using mobile phones to support agricultural-information sharing. In the methodology section, we go deeper into the case of Rwanda, including data gathering and processing approach. The results section presents identified farmer typologies that we link to the use of mobile phones in discussions. We also make concluding remarks at the end.

2 Theoretical background and hypotheses

2.1 Farm heterogeneity perspective

The agricultural sector has experienced substantial structural changes in terms of farm size, farm fragmentation, and farming system diversification (Sevik et al. 2021). These structural changes have significant effects on productivity and farming efficiency (Chavas, 2001). Jackson-Smith (1999) and Saint-Cyr (2017) showed that accounting for heterogeneity may be crucial to fully understanding the structural changes in farming because they stem from individual farmers' decisions. Farms' heterogeneity leads to multifaceted agricultural systems, thereby complicating the scaling of agricultural innovations (Weersink, 2018). The diversity in farms and farming systems also extends to the type of technologies employed on these farms. Large export-oriented farms will employ more capital-intensive technologies, but on small subsistence farms, manual labor and simple tools will more often be used. The fact that farms are heterogeneous, even within the context of the smallholder farming system of Africa, has been well documented (Bidogeza et al. 2009; Nabahungu & Visser, 2011; Tittonell et al. 2005).

In this study, we assume that ICT-based tools and mobile phones can also be viewed as a kind of production technology, as we hypothesize that.

H1 *Farm types are distinct and differentiated by the use of both basic and smart mobile devices,*

Although Folitse et al. (2019) and Hoang (2020) have discussed the pros and cons of farmers using mobile phones, studies differentiating between the use of basic and smart mobile phones are scarce. It is very important to differentiate basic mobile phones from smartphones, especially in developing countries, for several reasons, especially regarding subsistence smallholder farmers. Smartphones, in addition to being expensive compared to basic phones, are also regarded as miniature computers that can place and receive calls, therefore requiring a certain level of ICT literacy. This fact implies that smartphones might be used for functions other than mere communication, such as security, financial transactions, internet browsing, and video conferencing. All these functions require a relatively higher literacy skill to operate. Basic phones, on the other hand, are cheap and easy to operate and can satisfy the need of getting in touch through simple calls and messaging.

2.2 Determinants of farmers' mobile phone use

The upsurge in empirical studies provides insights into the factors that determine the use of mobile phones. Transactions costs, perceived profitability, credit constraints, operational skills, the high price of mobile phones, and network failure are mentioned as bottlenecks hindering the use of mobile phones, the main form of ICT, in agricultural production (Abay et al. 2016; Folitse et al. 2019; Minten et al. 2013). Some determining factors discussed in the literature are presented as limiting factors. However, it is crucial to understand that cases in developed countries might be far different from those in developing countries. For example, farmers in Ghana indicated network failure and the high price of mobile phones were the largest hindrances to mobile phone use (Folitse et al. 2019), but in Germany, computer literacy is one of the most important predictors of smartphone use in agriculture (Michels et al. 2020). Regarding determinants of mobile phone use, Folitse et al. (2019) showed a significant association between mobile phone use and demographic variables such as age, education, gender, and land size. Tadesse and Bahiigwa (2015) and Muto and Yamano (2009) also showed that younger and educated farmers are more likely to own and use mobile phones in agriculture than older and relatively low-educated farmers. Folitse et al. (2019) and Michels et al. (2020) agreed that older farmers were less likely to own and use mobile phones and more educated farmers were more likely to own and use mobile phones, because younger generations were more interested in new technologies and educated farmers could easily acquire basic ICT operational skills. Muto and Yamano (2009) showed that in Uganda, telecommunication companies establish mobile networks more often in big cities, where the economy is advanced and the population density is high, indicating that economic status and household income are among the most important determinants for owning and using mobile phones in developing countries. The household behavior theory suggests that household decisions are described by a utility function, which is maximized for farm production and cash flow constraints (Arthur & van Kooten, 1985; Lancaster, 1975). With this theory in mind, we formulated two more hypotheses:

H2a *Farmers with higher income and more education are likely to own and use mobile phones.*

H2b *Younger farmers are more likely to own and use mobile phones.*

3 Methodology

3.1 Study area, sampling, and data

We conducted this study in Rwanda, East Africa. We used data from a household survey that trained enumerators conducted from July to August 2018. We collected farmer-household information through the survey using a structured questionnaire in eight districts: Burera, Rulindo, Gatsibo, Kayonza, Gisagara, Muhanga, Karongi, and Rubavu. Following a stratified sampling approach, we purposively selected these districts for their representation of the major agro-ecological zones and of various types of banana-producing farmers within four provinces in Rwanda. We selected districts based on expert knowledge (mainly through multiple consultations with the banana program leader at the Rwanda Agriculture and Animal Resources Development Board (RAB) and raw data from a countrywide rapid assessment of Banana Xanthomonas wilt (BXW) status, which the RAB conducted between 2017 and 2018). Figure 1 summarizes districts' coverage of the main agro-ecological zones, and Table 1 summarizes the area covered by bananas in respective districts. We selected sectors and cells, low-level administrative units, based on expert input from the district and sector agronomists. The sampling team aimed for the selection of villages within a minimum distance of 5 km. As a result, we interviewed 690 farmers from 138 villages.

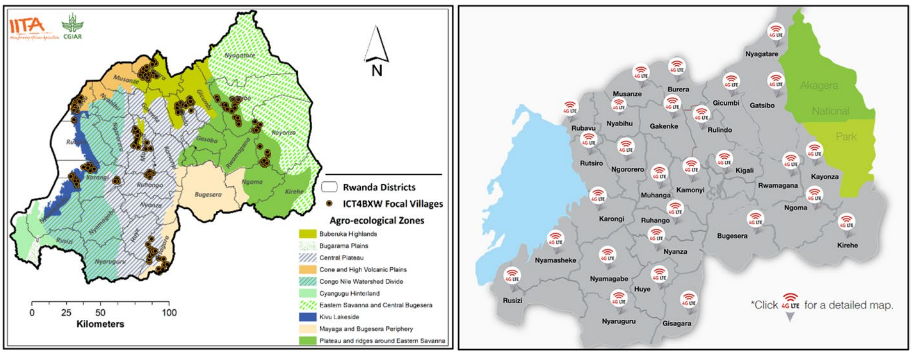

Fig. 1 Study area and mobile network coverage maps (https://www.ktrn.rw/coveragemap)

Table 1 Main characteristics of studied districts. *Source*: (NISR, 2017)

District	Cultivated area (ha)	Total B. area (ha)	C.B. area (ha)	B.B. area (ha)	Prop. banana land (%)
Burera	28,100	2341	806	1317	8.3
Rulindo	25,146	7835	1613	4182	31.2
Gatsibo	52,860	16,307	8365	5227	30.8
Kayonza	48,857	15,318	11,540	2497	31.4
Gisagara	28,867	9802	2146	6218	34.0
Muhanga	30,565	13,394	1760	9051	43.8
Karongi	21,361	8465	797	6793	39.6
Rubavu	17,153	953	683	187	5.6

B. Banana, *C.B* Cooking banana, *B.B.* Beer banana, *Prop.* Proportion of land allocated to bananas over the total cultivated area

Most questions in the questionnaire were closed-ended questions, such as multiple-choice and numerical questions. The questionnaire covered a wide range of categories of variables, such as socioeconomics, production systems, advisory services, and ICT in agriculture. For this study, we used data related to socioeconomic characteristics of farmers, banana production system characteristics, and extension services to develop farmer typology. At the same time, we used variables such as ownership and use of mobile phones, the relevance of ICTs in BXW management, and challenges farmers face in using ICTs in agriculture to describe the use of mobile phones among farmers, hypothesized to be affected by farmers' heterogeneity, recapitulated in the farm typology.

To develop farm typology, we started with around 60 variables selected based on the literature review and expert judgment, which is the most common method used when deciding which raw variables to start with (Bidogeza et al. 2009). We then subjected selected variables to further filtering in three steps to identify variables contributing most to the variance. The first step was to identify highly correlated variables. Once we found them, we removed them, as they carried redundant information (Alvarez et al. 2014). The second step was to identify possible outliers in the dataset by plotting out boxplots and histograms. We determined whether the identified outliers were outstanding values or typing errors and then dealt with them accordingly. The third step was to identify variables possibly measuring the same thing by determining whether they had the same sign in various components. We conducted a principal component analysis (PCA) and determined between the two correlated variables the one with less contribution to the first five components. The screening of variables was systematic; that is to say, we removed one variable at a time and then conducted another PCA to observe changes. We identified 12 variables as most contributing to the heterogeneity of banana farmers (Table 2).

As key target variables, we collected data related to the use of mobile phones using three questions: 1) "What type of mobile phone do you own?" followed by "What type (smart type, basic type, or none) of mobile phone did you use in the past three months?" 2) "What barriers (awareness of existence of ICT-based agricultural services = awareness, ICT-based agricultural services not available = availability, not know-how to use ICT-based agricultural services = know-how, ICT-based agricultural services not in local language = language, low literacy level = literacy, mobile devices and ICT-based agricultural

Table 2 Variables selected to be included in the PCA

Variable	Units	Average
Tropical livestock unit	Number	0.94 ± 0.91
Income from banana	Rwandan Francs*1000	70.2 ± 52.7
No. of people talked to about BXW	Number	10.7 ± 8.87
Nutrition diversity	Number	5.15 ± 1.98
Number of extension visits	Number	1.55 ± 0.82
Education years	Number	6.06 ± 3.34
Proportion of:		
Land allocated to cooking bananas	Percentage	14.4 ± 24.6
Cooking bananas consumed	Percentage	17.7 ± 32.2
Cooking bananas sold	Percentage	12.5 ± 25.7
Land allocated to beer bananas	Percentage	22.2 ± 28.5
Beer bananas consumed	Percentage	7.9 ± 22.3
Beer bananas sold	Percentage	38.4 ± 45.3

*the average value of income from bananas is to be multiplied by 1000 (70,200±52,700 Rwandan Francs)

services being expensive = expensive, and others) do you experience when using ICT-based agricultural services? 3) "How useful (neutral, not useful, somewhat unuseful, somewhat useful, very useful) is the use of these mobile services currently for your work as a banana farmer?" Table 3 summarizes the responses concerning the use of mobile phones among interviewed farmers. We also collected data on other socioeconomic variables, such as gender, age, and education.

This study targeted banana farmers distributed in contrasting agro-ecological zones (Fig. 1). Most (53%) farmers were between 25 and 50 years. Most respondents were male (60%) and married (84%), with a mean household size of five people. Most respondents (68%) had also attained a primary level of education. Furthermore, most respondents (80%) owned basic phones, and only 4% owned smartphones. Most respondents (70%) did not have off-farm income sources, and 44% solely grew bananas as crops. Regarding the grown banana types, 82% grew at least some cooking bananas on their plantation, and 57% grew some beer bananas. In terms of livestock endowment, 64% of farmers had cattle, 43% had goats, 21% had pigs, and 35% had chickens. Farmers may have several types of bananas and livestock animals.

3.2 Principal component analysis and cluster analysis

We used exploratory PCA and hierarchical cluster analysis to develop farm typologies with selected variables. We applied the Kaiser rule, which says that retained components are those with eigenvalues (λ) > 1 (Jackson, 1993), to identify principal components and conduct further cluster analysis. We retained five components having eigenvalues (λ) > 1 and explaining 63.3% of the total variance. Using factor loadings, it is possible to identify variables that explain the component most and would describe it.

Figure 2a shows the scree plot highlighting 10 components from the 12 variables that we included in the PCA, with five components having eigenvalues greater than 1 retained for cluster analysis and explaining about 63% of the total variation. Figure 2b presents variables' contributions to the construction of two main components (explaining about 33% of

Table 3 Summary of the use of mobile phones among farmers

Type of variable	Name of variable	Categories	Frequency	% of respondents
Ownership	Own smartphone	Yes (=1)	30	4.3
		No (=0)	660	95.7
	Own basic phone	Yes (=1)	494	71.6
		No (=0)	196	28.4
	No phone	Yes (=1)	190	27.5
		No (=0)	500	72.5
Use	Used smartphone	Yes (=1)	27	3.9
		No (=0)	663	96.1
	Used basic phone	Yes (=1)	550	79.7
		No (=0)	140	20.3
Barriers to the use of ICT-based agricultural services	Awareness	Yes (=1)	360	52.2
		No (=0)	330	47.8
	Availability	Yes (=1)	37	5.4
		No (=0)	653	94.6
	Know-how	Yes (=1)	256	37.1
		No (=0)	434	62.9
	Language	Yes (=1)	25	3.6
		No (=0)	665	96.4
	Literacy	Yes (=1)	36	5.2
		No (=0)	654	94.8
	Expensive	Yes (=1)	91	13.2
		No (=0)	599	86.8
	Others	Yes (=1)	119	17.2
		No (=0)	571	82.8
Usefulness	Usefulness	Not useful (=1)	79	11.4
		Somewhat un-useful (=2)	24	3.5
		Neutral (=3)	123	17.8
		Somewhat useful (=4)	368	53.3
		Very useful (=5)	96	13.9

variation) where land allocated to beer banana or cooking banana was the main contributing variables.

We subjected the five components retained to hierarchical cluster analysis. Cluster analysis is a method of grouping dataset objects into groups with similarities (Penkova, 2017). We thus generated a dendrogram (Fig. 3a) with the sequence in which farmers were merged. The dendrogram provides a default cutting line, and it allows us to adjust the cutting lines based on the visualization, resulting in a different number of clusters. Using the default cutting line, we generated three distinct clusters, visualized in Fig. 3b. Clusters 1 and 2 are distinct, whereas cluster 3, although distinct in particular elements, shares some characteristics with clusters 1 and 2 (Fig. 2b).

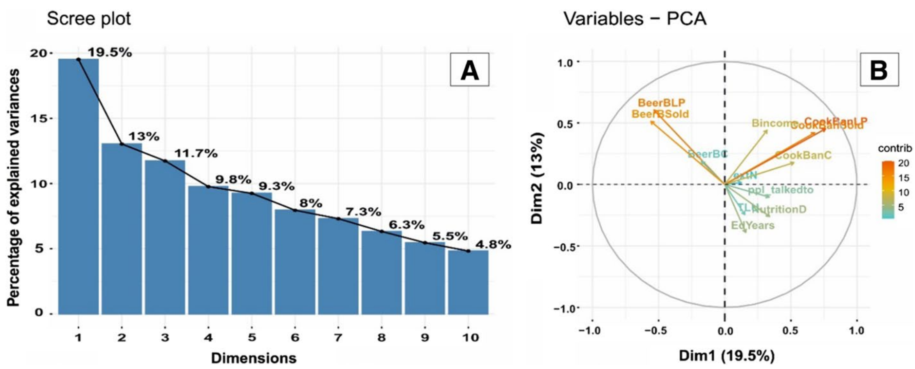

Fig. 2 PCA scree plot (**A**) and variables' contributions to components (**B**). *Note* NutritionD = Nutrition diversity, extN = Number of extension visits, EdYears = Education Years, TLU = Tropical Livestock Unit, CookBanLP = Proportion of land allocated to cooking banana, CookBanC = Proportion of cooking banana consumed, CookBanSold = Proportion of cooking banana sold, BeerBLP = Proportion of land allocated to beer banana, BeerBC = Proportion of beer banana consumed, BeerBSold = Proportion of beer banana sold, Bincome = Income from banana, ppl_talkedto = No. of people talked to about BXW

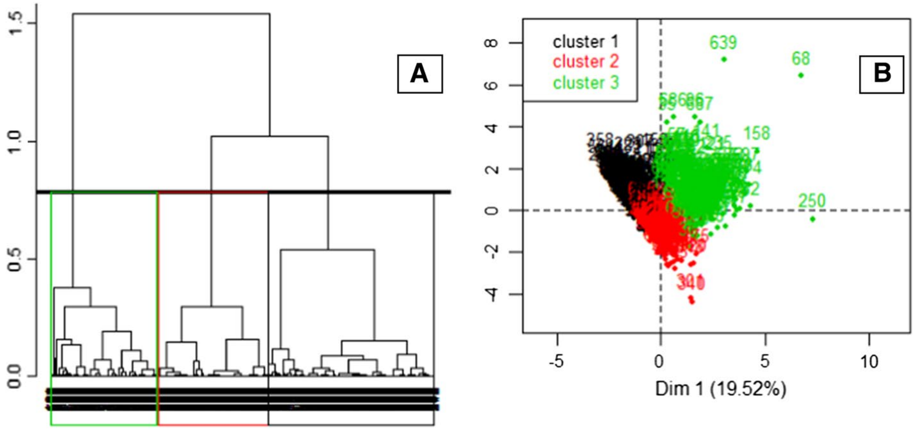

Fig. 3 Cluster dendrogram and clusters graphic representation

3.3 Logistic regression models

We analyzed data using statistical package R version 4.0.3 (Kaya et al. 2019; Team, 2021). We also derived and reported descriptive statistics. To examine the relationship between the outcome variable (dependent) and predictor variables (independent), we applied logistic regression models (Menard, 2002). Logistic regression is used to obtain a statistic (odds ratio) that quantifies the strength of the association between two events in the presence of more than one explanatory variable (Sperandei, 2014). Our outcome variables were the use of mobile phones (1: using or 0: not using), barriers to the use of mobile phones (a farmer considering a certain aspect a barrier or not), and perceived usefulness of mobile phones (whether each farmer considered a specified level of usefulness sufficient or not). Our predictor variables were farm type as well as farmer's gender, level of education, level of income from bananas, and age category. The selected independent variables portray the heterogeneity among banana farmers. The nature of data (responses) dictated the type of logistic regression model that we applied. A logistic regression can be binomial, ordinal, or multinomial. Our data, as described in Sect. 3.3, show that the use and barriers to the use of mobile phones are binary variables; therefore, we analyzed the data using binomial logistic regression. In this case, we coded the outcome as "0" or "1" (0 = not using, 1 = using), as this coding leads to the most straightforward interpretation. This analysis allows us to estimate how perturbations in model parameters affect the probability that a certain binary outcome will occur (Morotti & Grandi, 2017). Using the outcome variable "Own smartphone" as an example, the final model is given by the following equation:

$$\mathrm{p_k(Own\ smartphone)} = \begin{cases} \left(\frac{1}{1+e^{-z_k}}\right) \text{for Own smartphone}_k = 1 \\ \left(1-\frac{1}{1+e^{-z_k}}\right) \text{for Own smartphone}_k = 0 \end{cases}$$

with

$$\mathrm{z_k} = \beta_0 + \beta_1 \times \mathrm{Types} + \beta_2\ \mathrm{Gender} + \beta_3 \times \mathrm{Education} + \beta_4 \times \mathrm{Income} + \beta_5 \times \mathrm{Age}$$

βi are the regression coefficients associated with the independent variables. In this case, we are modeling the outcome "own smartphone" as predicted by farm typology, gender, education, income from bananas, and age category.

Concerning the perceived usefulness of mobile phones, data were recorded as five ordinal responses; therefore, we applied an ordinal logistic regression. Results have been interpreted based on odds ratios. For estimation, we use the ordered logit model with the following structure:

$$\begin{aligned} logit(P(Y \le j)) = log\left[\frac{P(Y \le j)}{1 - P(Y > j)}\right] \\ = \alpha_j + \beta_1 \times \mathrm{Types} + \beta_2\ \mathrm{Gender} \\ + \beta_3 \times \mathrm{Education} + \beta_4 \times \mathrm{Income} + \beta_5 \times \mathrm{Age} \end{aligned}$$

where Y is the response variable with j^{th} category, αj is the intercept parameter, βk are the parameters related to each explanatory variable explaining the effect of that explanatory variable on the response variable, and *P()* are the cumulative probabilities for a j^{th} category.

We used the likelihood ratio to test the goodness of fit of our models and used the dominance analysis to determine the predictors' importance in the model (Azen & Traxel, 2009).

We present odds ratios showing the probability of an event (on outcome variable) to happen compared to the selected reference group of predictor variables. Reference groups were beer banana farm type, female, none educated, farmers with zero income from bananas, and young (< 30 years old) farmers for farm typologies, gender, education, level of income from bananas, and the age category of our independent variables, respectively. The likelihood ratio shows a significant improvement in the fit of the full model over the null model. In the Hosmer Lemeshow goodness of fit test, the *p* value of our models ranged between 0.34 and 0.99, indicating no evidence of poor fit.

Table 4 Variables associated with farm heterogeneity and resulting clusters

Variable	V.test mean C1	V.test mean C2	V.test mean C3
Nutrition diversity	− 5.12	2.55	2.89
Number of extension visits	− 2.02	–	–
Education years	− 3.10	2.91	–
Tropical livestock unit	− 2.56	3.38	–
Income from bananas	–	− 4.94	5.77
No. of people talked to	− 4.15	–	3.95
Proportion of:			
Land allocated to cooking bananas	− 11.20	− 8.38	20.62
Cooking bananas consumed	− 9.13	− 7.81	17.81
Cooking bananas sold	− 9.60	− 8.26	18.78
Land allocated to beer bananas	16.77	− 12.41	− 5.30
Beer bananas consumed	6.39	− 5.60	–
Beer bananas sold	19.45	− 14.27	− 6.27
Named according to V.test	Beer banana farm type (BBF)	Livestock-based farm type (LBF)	Cooking banana farm type (CBF)

4 Results

4.1 Principal component analysis and clustering results

In Table 4, we present identified variables associated with farm heterogeneities, which can be summarized in three groups: respondent characteristics (nutrition diversity and education years); type of banana grown, distribution in the field, and use (cooking or beer banana with their respective proportion of allocated land, banana income, and proportion sold and consumed); and access to extension services (number of extension visits and people talked to). By observing the v.test values, which indicate if the mean of the cluster is lower or greater than the overall mean, we find three farm types. Type one is more associated with the proportion of beer bananas sold, the proportion of land allocated to beer bananas, and the proportion of beer bananas consumed. Thus, we named it beer banana farm type (BBF). The second type is more associated with tropical livestock units (livestock numbers converted to a common unit), education years, and nutrition diversity. We named it livestock-based farm type (LBF). The third is named cooking banana farm type (CBF) because it is mostly associated with the proportion of land allocated to cooking bananas and the proportion of cooking bananas sold and consumed.

Figure 4 provides descriptions of the resulting farm types and associated variables included in regression models. Concerning education level, most farmers attained a primary level of formal education across all farm types. However, relatively more cooking banana farmers had attained secondary education. The low level of income from bananas was between 1,000 and 20,000 Rwandan francs (1 Rwandan franc = 0.00096 USD), whereas high levels were above 20,000 francs. The beer banana farm type had more high-income farmers. However, most farmers across all types did not attain cash income from bananas. This implied that most farmers were subsistence farmers who grew bananas for self-consumption. From the age category chart, the majority of farmers were older (above

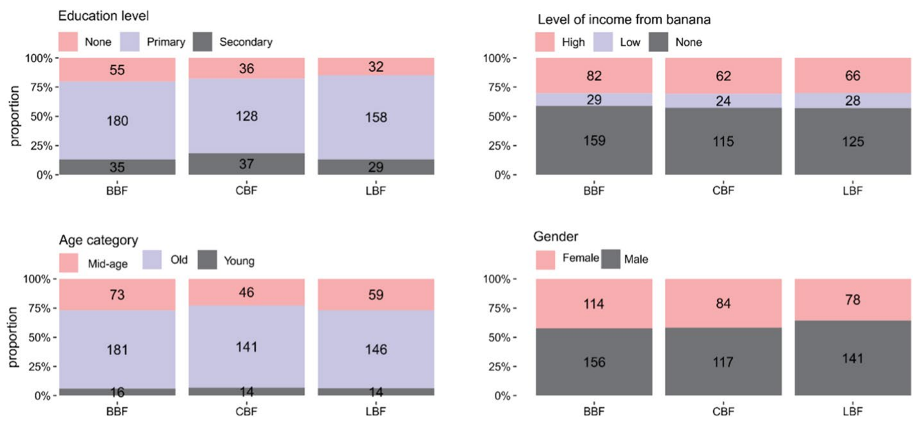

Fig. 4 Description of households and respondents by banana farm typologies—BBF: beer banana farmers, CBF: cooking banana farmers, LBF: livestock-based banana farmers

50 years). On the other hand, most respondents were males, and the livestock-based farm type had fewer females than the rest of the farmer types.

Table 5 Odds ratios and standard error (in parentheses) for the binary logistic regression model for owning and using mobile phones

Predictor variables	Own smart P	Own basic P	No phone	Used smart P	Used basic P
Cooking banana farm type	2.5641**	2.1174***	0.4249***	3.1237**	2.3302***
	(0.4620)	(0.2270)	(0.2339)	(0.5106)	(0.2564)
Livestock-based farm type	1.0369	1.5274**	0.6786*	1.4403	1.6554**
	(0.5376)	(0.2115)	(0.2129)	(0.5756)	(0.2332)
Male farmers	0.8008	2.1214***	0.4713***	0.7829	1.0700
	(0.3991)	(0.1856)	(0.1884)	(0.4189)	(0.2082)
Primary education	4.6078	3.1304***	0.3025***	3.8172	3.4477***
	(1.0427)	(0.2185)	(0.2198)	(1.0496)	(0.2299)
Secondary education	19.6619***	7.7792***	0.1053***	19.3225***	8.6930***
	(1.0552)	(0.3579)	(0.3776)	(1.0547)	(0.4212)
High banana income	0.7472	0.8568	1.2084	1.2811	0.7586
	(0.4675)	(0.2004)	(0.2029)	(0.4525)	(0.2204)
Low banana income	1.5315	0.6920	1.4437	1.6197	0.6727
	(0.5452)	(0.2931)	(0.2988)	(0.6073)	(0.3162)
Middle-aged farmers	4.1449	1.4949	0.6888	3.3493	1.9893*
	(1.0721)	(0.3781)	(0.3859)	(1.0971)	(0.3983)
Older farmers	1.7755	1.8765*	0.5640	1.9016	2.4066**
	(1.0540)	(0.3542)	(0.3616)	(1.0633)	(0.3713)
Constant	0.0027***	0.2814***	3.4231***	0.0020***	0.4917
	(1.4910)	(0.4187)	(0.4254)	(1.5245)	(0.4354)

Variables with "*", "**", and "***" are significant at 1%, 5% and 10% significance levels

Table 6 Odds ratios and standard error (in parentheses) for the binary logistic regression model for barriers to using mobile phone-based agricultural services

Predictor variables	Awareness	Availability	Know-how	Language	Literacy	Expense	Others
Cooking banana farm type	0.6848**	0.6718	0.6346**	1.4674	0.6837	0.8448	1.9338***
	(0.1901)	(0.4544)	(0.2010)	(0.4964)	(0.4539)	(0.2872)	(0.2491)
Livestock-based farm type	0.7453	1.0320	0.7212*	0.8269	0.9620	0.7846	1.3751
	(0.1859)	(0.3895)	(0.1927)	(0.5229)	(0.4145)	(0.2796)	(0.2580)
Male farmers	1.1226	1.5174	2.2577***	15.5018***	0.6465	3.4910***	0.5046***
	(0.1624)	(0.3917)	(0.1748)	(1.0279)	(0.3664)	(0.3032)	(0.2133)
Primary education	1.1534	7.8881**	1.6051**	4.3155	0.2101***	8.3141***	1.1157
	(0.2092)	(1.0249)	(0.2306)	(1.0362)	(0.3766)	(0.7289)	(0.2844)
Secondary education	0.7062	3.4524	1.3219	2.0048	0.1217***	14.8250***	1.6725
	(0.2754)	(1.1667)	(0.2999)	(1.2439)	(0.7657)	(0.7600)	(0.3465)
High banana income	1.1534	0.4595*	1.1730	0.6348	0.2988**	0.7457	1.0508
	(0.1738)	(0.4672)	(0.1818)	(0.5271)	(0.5053)	(0.2843)	(0.2324)
Low banana income	0.4802***	1.0575	0.8623	0.6698	0.8494	1.4580	1.7559*
	(0.2573)	(0.4864)	(0.2610)	(0.6503)	(0.5732)	(0.3198)	(0.3104)
Middle-aged farmers	1.5296	0.4853	1.5986	1.3350	1.4480	0.9204	0.9432
	(0.3448)	(0.6482)	(0.3807)	(0.8137)	(1.0857)	(0.4871)	(0.4281)
Older farmers	1.4349	0.6106	1.8125*	0.6418	1.8805	0.9120	0.7308
	(0.3223)	(0.5727)	(0.3580)	(0.7921)	(1.0442)	(0.4495)	(0.4010)
Constant	0.8726	0.0154***	0.1770***	0.0015***	0.1854	0.0101***	0.2164***
	(0.3833)	(1.1770)	(0.4290)	(1.5910)	(1.0885)	(0.8747)	(0.4917)

Variables with "*", "**", and "***" are significant at 1%, 5% and 10% significance levels

Table 7 Odds ratios and standard error (in parentheses) for the ordinal logistic regression model for farmers' perception of usefulness of mobile phones in agriculture

Variable category	Variable name	Odds ratios and S.E
Outcome	ICT perceived as somewhat un-useful (Order 2)	12.9778*** (0.3121)
	Neutral (Order 3)	1.6548** (0.2558)
	ICT perceived as somewhat useful (Order 4)	0.8896 (0.2559)
	ICT perceived as very useful (Order 5)	0.0606*** (0.2786)
Predictor	Cooking banana farmers	1.0925 (0.1812)
	Livestock-based farmers	1.1988 (0.1714)
	Male farmers	0.8765 (0.1546)
	Primary education	3.1594*** (0.1928)
	Secondary education	5.5363*** (0.2668)
	High banana income	1.0116 (0.2519)
	Low banana income	0.9061 (0.1641)
	Middle-aged farmers	0.9026 (0.1682)
	Older farmers	0.7917 (0.3111)

Variables with "*", "**", and "***" are significant at 1%, 5% and 10% significance levels

4.2 Regression analysis results

In Tables 5, 6, and 7, we present regression results on ownership and use of mobile phones by farmer typologies (Table 5), barriers for mobile phone use (Table 6), and perceived usefulness of mobile phone-based agricultural services (Table 7).

4.2.1 Ownership and use of mobile phones

Results from Table 5 show that farm type, gender, education, and age significantly affected the likelihood of owning or using mobile phones. Cooking banana farmers and farmers with a secondary level of education were likely to own and use both smart and basic phones. Livestock-based, male, primary-educated, and older farmers were more likely to own and use basic phones. However, income from bananas had little effect on the likelihood of owning or using mobile phones.

4.2.2 Barriers in using mobile phone-based agricultural services

Results in Table 6 show that cooking banana farmers were less likely to be limited by the lack of awareness of existing mobile phone-based agricultural services and technical know-how. Farmers on livestock-based farm types were also less likely to be limited by technical know-how. Surprisingly, male farmers were more likely to be limited by the lack of technical know-how, devices being expensive, and language barriers. On the other hand, farmers with primary education were more likely to be limited by the availability of phone-based agricultural services, devices being expensive, and lack of technical know-how, yet farmers with secondary education were more likely to only be limited by devices being expensive. However, farmers with both primary and secondary education were less likely to be limited by ICT literacy levels compared to uneducated farmers. Farmers who earned high banana incomes were also less likely to be limited by ICT literacy levels and the availability of ICT services compared to subsistence farmers. On the other hand, farmers with low income from bananas were less likely to be limited by a lack of awareness of the existence of mobile phone-based agricultural services compared to subsistence farmers. Unsurprisingly, older farmers were more likely to be limited by a lack of technical know-how concerning mobile phone-based agricultural services compared to younger ones.

4.2.3 Perceived usefulness of mobile phones in agriculture

Results in Table 7 are responses to the question "To what extent do farmers currently find mobile phone services useful for their work as banana farmers?" The main factor influencing the perceived usefulness of mobile phones in agriculture was education level. Both primary and secondary education are more likely to recognize the usefulness of mobile phones, compared to farmers without education.

5 Discussion

In this study, we evaluated ownership and use of mobile phones among banana farmers in Rwanda, considering farmers' heterogeneity. Specifically, we assessed how different farm types are associated with the use of mobile phones, studied barriers to the use of mobile phones, and analyzed the farmers' perceived usefulness of using digital technologies. Generally, our results confirm that farmers' heterogeneity is associated with the ownership and use of both basic and smart mobile phones among farmers. The most prominent factors associated with mobile phone usage are education, farm type, and gender. Moreover, we provided empirical evidence to support future interventions vis-à-vis the use of mobile phone-based agricultural services.

5.1 Hypotheses

In Sect. 2, we proposed a few hypotheses. Here, we evaluate them to see how these hypotheses hold based on our results.

H1: Farm types are distinct and differentiated by the use of both basic and smart mobile devices

Given the analysis results, we accept hypothesis H1. First, we found that banana farmers are heterogeneous and can be grouped mainly by their main production systems into three types: beer banana farmers, cooking banana farmers, and livestock-based farmers. Differences in banana farming systems might be partially attributed to the differences in production environment, such as soil and climate, as well as the culture of the community (Cetin et al. 2018; Nsabimana et al. 2008; Verdoodt & Van Ranst, 2003). Different types of farmers in contrasting farming contexts may well have diverging preferences in the adoption of innovations (Blazy et al. 2009).

Second, we found that different types of banana farmers differed in their ownership and use of mobile phones. Cooking banana farmers were more likely to own and use both basic and smartphones, livestock-based farmers were more likely to own and use basic phones, and beer banana farmers were less likely to own and use mobile phones. Our results show that the cooking banana farm type is more ready to use phone-based digital tools for agronomic advice than the rest of the banana farm groups (McCampbell et al. 2021).

Given low levels of education among our surveyed farmers, it makes sense that basic phones, which require minimal literacy skills, are significantly preferred. Requiring only simple skills to make calls or read short messages, basic phones enable farmers to connect with extension agents. At the same time, basic phones might disable another group due to limited literacy skills or income-related factors; thus, we agree that farm types are distinguishable based on ownership and use of basic mobile phones.

We distinguished ownership of basic and smart mobile phones with the argument that the need for communication, which is universal according to Maslow's hierarchy of needs, creates an equal prospect to own and use basic phones. Therefore, limited literacy skills in our sample would have rendered our high-income sample not significantly likely to own and use smartphones. Even though Kang and Jung (2014) argued that the need for safety and self-actualization predicted the propensity to own and use smartphones in the USA and Korea, these prepositions could not be generalized to low-literacy farmers in developing countries.

H2a *Farmers with higher income and more education are likely to own and use mobile phones*

We assumed that income from bananas could influence ownership and use of mobile phones. However, our results did not support this hypothesis. The possible reason for this might be that we only used income categorically, unlike other studies that found a positive income effect. Furthermore, we did not use all household income from all possible sources (other agricultural activities, off-farm income, remittances, etc.). It is important to note that agriculture in Rwanda is dominantly subsistence, and most of our respondents had zero income. Nevertheless, although our regression model does not show a significant association of income from bananas with ownership and use of mobile phones, the group with the highest proportion (31%) of farmers in the high-income category (cooking banana farmers) had a higher likelihood of owning and using both basic and smart mobile phones.

Our results contradict most existing studies, which showed that owning a mobile phone is positively associated with income (Hoang, 2020; Katz & Aspden, 1998; Pierpaoli et al. 2013; Sekabira & Qaim, 2017; Tadesse & Bahiigwa, 2015). However, our results partially agree with Forenbacher et al. (2019), who did not find significant evidence that income is associated with mobile phone ownership.

As for the hypothesis on the education level, our results are in line with most previous findings (Folitse et al. 2019; Forenbacher et al. 2019; Michels et al. 2020). We confirmed that farmers with higher education were more likely to own and use mobile phones, although most farmers we interviewed had relatively low levels of education. The use of mobile phones requires some literacy basics, such as being able to read and write to make calls or read text messages. In our sample, we observed that nearly 83% of farmers had not gone beyond primary school, suggesting that the sample was very low on literacy basics. Furthermore, it is important to note that mobile phones currently do not support Kinyarwanda, a Rwandan local language, except for a few applications. Therefore, basic literacy skills were necessary to use mobile phones, hence supporting H2a.

H2b: Younger farmers are more likely to own and use mobile phones

Our results show that older farmers were more likely to own and use basic mobile phones compared to younger farmers, which contradicts existing studies (e.g., Michels et al. (2020). This is surprising even though younger farmers were less likely to be restricted by technical know-how in using mobile phones (as shown in Table 6). The reason might be that younger farmers, especially those with higher education levels, are less willing to engage in agriculture and more likely to migrate to cities and take off-farm jobs. Hence, fewer highly educated young farmers are engaged in banana farming. This is clearly illustrated in Fig. 4a—all three types of banana farms involved less than 7% of young farmers. This sampling bias may have distorted the estimation.

5.2 Challenges of using mobile phone-based agricultural services and the relevance of mobile phones in agriculture

The main barriers banana farmers experienced in using mobile phone-based agricultural services are interrelated, to some extent—for example, the lack of awareness of the existence of mobile phone-based agricultural services, and the limited availability of such ICT-based services. However, we believe that farmers who indicated that they were restricted by the limited availability of ICT services had a certain level of interest in looking for these services. The same applies to farmers who indicated that they were restricted by technical know-how and those who were limited by low levels of ICT literacy. We argue that those who were limited by the level of ICT literacy seemed to be aware of a certain level of ICT literacy that they did not have. Therefore, most of the barriers farmers faced were largely related to low levels of education. Specifically, beer banana farmers, older farmers, uneducated farmers, and subsistence farmers were disadvantaged concerning the use of mobile phone-based agricultural services. Moreover, uneducated farmers were more likely to perceive the use of mobile phones in agriculture as irrelevant. Network failure, which was identified by Folitse et al. (2019) as the major constraint to the use of mobile phones in Ghana, was not such an important factor because the mobile phone network in Rwanda is relatively reliable.

5.3 Policy implications

Our findings provide reliable empirical evidence to effectively guide and customize agricultural policy formulation with regards to using ICT-based services in agriculture. Specifically, we provide evidence supporting mobile phone-based service interventions for future agricultural digitalization. Farm-type categories should be used in tailoring the most fit interventions, thus effectively moving away from the one-size-fits-all extension model that has been criticized for hampering the adoption of innovations (Coe et al. 2019; Hammond et al. 2017). Our results suggest that raising the level of education is key to overcoming most barriers that banana farmers face with regards to using mobile phone-based agricultural services. Nevertheless, the lack of awareness of the existence of such ICT services points to the need for wider public sensitization to these services. Furthermore, in line with making these services more customizable to enhance adoption, we suggest that agricultural-based mobile applications should have the option of being used in a local language, which enable use by those with low-literacy skills.

Another key to successful agricultural digitalization is youth involvement. Our results show that older farmers were more likely to be limited by a lack of technical know-how, which would not be the case for younger farmers. Furthermore, the young generation in Rwanda has been benefiting from a low-cost education program since 2010. Enticing and integrating young people in agriculture from an early age would be a strategic way to bridge the education–skills gap observed among farmers. Strategies that facilitate easy access to smartphones for young farmers should be designed and put in place. Perhaps older farmers would even easily acquire digital skills from their younger colleagues.

6 Conclusion

By analyzing factors associated with owning and using mobile phones among banana farmers, we contribute to understanding the tendency for the use of mobile phones among rural smallholder farmers that dominate the agricultural sector in developing countries. To do so, first, we identified three distinct types of banana farmers: beer banana farm type, cooking banana farm type, and livestock-based farm type. Second, we demonstrated that identified banana farm types are distinguishable by how farmers used mobile phones as related to agriculture. Owning and using mobile phones was associated with farm type and several farmer characteristics.

The results confirmed the hypothesis that farm types are distinct and differentiated by the use of mobile devices, including basic and smartphones. First, we found that banana growers are heterogeneous and distinguished by the main focus of their respective production systems: beer banana farmers, cooking banana farmers, and livestock-based farmers. Second, further analysis showed that cooking banana farmers were more likely to own and use both basic and smartphones, livestock-based farmers were more likely to own and use basic phones, and beer banana farmers were less likely to own and use mobile phones. Our regression model showed no significant association between income from bananas and ownership and use of mobile phones; however, the group with the highest proportion (31%) of farmers in the high-income category (cooking banana farmers) had a higher likelihood of owning and use both basic and smart mobile phones. Results confirmed that farmers with higher education were more likely to own and use mobile devices. Younger farmers were also more likely to own and use mobile phones. We found that age was associated with ownership and use of mobile devices; however, no significant indication was found that younger farmers had the propensity to own and use smartphones.

Furthermore, gender and education level were significantly associated with the perceived usefulness of mobile phones in agriculture. Challenges that inhibited the use of mobile phones were mostly related to low levels of farmers' education. With the results of this study, we provide strategically important insights for policy and practices concerning digital agriculture, especially with regards to understanding farmers' heterogeneity and use of mobile phones in agriculture. Hence, our results provide reliable empirical evidence upon which future interventions targeting the use of mobile phones to support agricultural systems could effectively be based. Moreover, inferences can be made with regards to other cropping systems that are similar in context to the systems we studied.

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