ICAE 2024

32nd International Conference of Agricultural Economists
2-7 August 2024 | New Delhi | India

Smallholder farmers' willingness to pay for digital agricultural extension services: Evidence from Tanzania and Burkina Faso

Cool Dady Mangole[1,2], Kelvin Mulungu[3], Christian Kamala Kaghoma[2], Maurice Tschopp[4] and Menale Kassie[1]

1: *International Centre of Insect Physiology and Ecology (icipe), Nairobi, Kenya*
2 : *Université Catholique de Bukavu (UCB), Bukavu, DR Congo*.
3: *International Maize and Wheat Improvement Center (CIMMYT), Lusaka, Zambia*
4: *Centre for Development and Environment (CDE), University of Bern, Switzerland*
Corresponding author email: mangolecool5@gmail.com dmangole@icipe.org

Abstract

Financial contributions from farmers are increasingly acknowledged as a sustainable mechanism for funding extension services. However, the literature on willingness to pay (WTP) for digital agricultural extension is limited. This study examines the willingness to pay and its determinants among Tanzania and Burkina Faso farmers for a novel digital extension platform named *farmbetter*, leveraging primary data. The *Becker-DeGroot-Marschak* (BDM) method was used to elicit the amount farmers are willing to pay. For variable selection and estimation of the marginal effects of the key determinants of WTP, we applied the Least Absolute Shrinkage and Selection Operator (Lasso) machine learning algorithm in tandem with the cross-fit partialing out Lasso regression. Our findings show that smallholder farmers are willing to pay USD 5.4 monthly for *farmbetter* service, with a median of USD 2.4. Specifically, farmers in Burkina Faso are willing to pay more than in Tanzania. Key determinants of WTP include gender, household labour force, group membership, contact with extension officers, farm-related stress, digital literacy, smartphone access, and usage of digital tools. These findings imply that investments in digital competencies, ensuring access to smartphones, and promoting participation in farmer organizations could significantly improve the demand for digital extension among farmers.

JEL Codes: Q12, Q16, R22

IAAE

Smallholder farmers' willingness to pay for digital agricultural extension services: Evidence from Tanzania and Burkina Faso

Cool Dady Mangole[1,2], Kelvin Mulungu[3], Christian Kamala Kaghoma[2], Maurice Tschopp[4] and Menale Kassie[1]

[1]International Centre of Insect Physiology and Ecology (icipe), Nairobi, Kenya

[2]Université Catholique de Bukavu (UCB), Bukavu, DR Congo.

[3]International Maize and Wheat Improvement Center (CIMMYT), Lusaka, Zambia

[4]Centre for Development and Environment (CDE), University of Bern, Switzerland

Abstract

Financial contributions from farmers are increasingly acknowledged as a sustainable mechanism for funding extension services. However, the literature on willingness to pay (WTP) for digital agricultural extension is limited. This study examines the willingness to pay and its determinants among Tanzania and Burkina Faso farmers for a novel digital extension platform named *farmbetter*, leveraging primary data. The *Becker-DeGroot-Marschak* (BDM) method was used to elicit the amount farmers are willing to pay. For variable selection and estimation of the marginal effects of the key determinants of WTP, we applied the Least Absolute Shrinkage and Selection Operator (Lasso) machine learning algorithm in tandem with the cross-fit partialing out Lasso regression. Our findings show that smallholder farmers are willing to pay USD 5.4 monthly for *farmbetter* service, with a median of USD 2.4. Specifically, farmers in Burkina Faso are willing to pay more than in Tanzania. Key determinants of WTP include gender, household labour force, group membership, contact with extension officers, farm-related stress, digital literacy, smartphone access, and usage of digital tools. These findings imply that investments in digital competencies, ensuring access to smartphones, and promoting participation in farmer organizations could significantly improve the demand for digital extension among farmers.

JEL codes: Q12, Q16, R22

Keywords: willingness to pay, farmbetter app, *Becker-DeGroot-Marschak* method, Lasso model, Tanzania, Burkina Faso.

1. Introduction

Agricultural extension services are critical in transforming farmers' behaviour and advancing agricultural development in sub-Saharan Africa (SSA) (Davis et al., 2012; Kiptot & Franzel, 2019; Kosim et al., 2021). These services are instrumental in disseminating knowledge and skills, enhancing awareness, and promoting the adoption of sustainable farming practices. They provide advice on a range of topics including agronomic practices, weather forecasts, and market trends (Sylla et al., 2019). Traditionally, these services have been delivered by agricultural extension officers through farmer field schools, training and visitation, and demonstrations (Bakker et al., 2021; Danso-Abbeam et al., 2018; Kiptot & Franzel, 2019; Kosim et al., 2021). Nonetheless, the prevailing extension system in many developing countries faces numerous challenges, such as insufficient infrastructure, budgetary constraints, and the remoteness of villages, which hinders the delivery of effective agricultural information to many farmers (Elapata et al., 2023; Lee et al., 2023; Sylla et al., 2019). Most SSA countries struggle to meet the recommended extension officer-to-farmer ratio (Fabregas, Kremer, & Schilbach, 2019; Samson Olayemi et al., 2021). For instance, Tanzania's ratio stands at 1:1,172, falling short of the World Bank recommended ratio 1:200-500 (Ndimbo et al., 2023). This gap resulted in about 90% of farming households receiving inadequate crop and livestock extension services in Tanzania (NSCA, 2021). In Burkina Faso, the number of extension officers has more than doubled from 1,688 extension officers in 2017 to 4,038 extension officers in 2019, suggesting a ratio of one extension agent for every 424 farm households. Despite this increase, the effectiveness of extension services remains relatively low due to a lack of financial resources (Mabaya et al, 2021). This highlights the urgent need for innovative, cost-effective, and farmer-centered extension approaches (Hidrobo et al., 2022; Kiptot & Franzel, 2019).

With the expansion of mobile phone usage in the SSA (FAO & ITU, 2022), mobile phone-based agricultural extension services are emerging as a viable alternative to traditional methods (Cole & Fernando, 2021; Fabregas et al. 2019, Hidrobo et al., 2022; Tambo et al., 2019). These services utilize SMS, interactive voice response (IVR), call center, mobile applications, and video to establish robust real-time connections between extension providers and farmers, ensuring timely and customized extension assistance even in isolated areas (Kante et al., 2019; Ragasa et al., 2021; Tambo et al., 2019). Evidence suggests that mobile phone-based extension services significantly increase the adoption of recommended farming practices and overall agriculture productivity

(Dhehibi et al., 2023; Issahaku et al., 2017; N. Khan et al., 2020; Munthali et al., 2018; Quandt et al., 2020; Silvestri et al., 2020; Witteveen et al., 2017). However, the scalability and sustainability of such services depend on the establishment of sound financial models (Bonke et al., 2018; Gray et al., 2018).

Financial contributions from farmers are increasingly acknowledged as a sustainable mechanism for funding extension services (Ozor et al., 2011; Sylla et al., 2019). Such contributions reduce the reliance on public and external funding sources, thereby enhancing the resilience and sustainability of the extension system (Ozor et al., 2011; Abed et al. 2020; Bonke et al., 2018). However, the effectiveness of this funding approach depends on farmers' acceptance and the value they perceive in the digital extension methods (Chia et al. 2019; Gosbert et al. 2019; Ozor et al., 2011). Policymakers must consider farmers' willingness to pay (WTP) as a pivotal factor when integrating financial contributions from farmers into the extension program (Gosbert et al., 2019). Therefore, conducting a thorough assessment of WTP is crucial (Gosbert et al. 2019) for designing effective pricing policies and establishing long-term financial strategies for digital extension services (Abebe, 2023; Chia et al. 2019).

Although there is ample evidence on farmers' WTP for conventional extension services in Africa (Abed et al., 2020; Badr et al. 2019; Sumo et al. 2023; Ulimwengu & Sanyal, 2011), the literature on WTP for digital agricultural extension is limited. Research in Ghana and Ethiopia indicates a positive attitude toward paying for digital extension, albeit with notable disparities such as a gender gap in WTP (Hidrobo et al. 2021; Abebe, 2023). Factors such as farmers' education level, mobile phone ownership, access to electricity, farmers' information-seeking behavior, and proximity to urban centers have all been positively associated with WTP for digital extension. However, these studies have not adequately addressed the influence of digital literacy and farm-related stress (e.g., crop diseases, pests, droughts, floods, etc.) on WTP. Kante et al. (2019) emphasize the importance of digital skills for utilizing digital farm input information, implying that smallholder farmers with limited digital literacy are likely to exhibit lower demand for digital extension services (Abdulai et al., 2023; McCampbell et al., 2021). Additionally, Abed et al. (2020) point out that the demand for extension services is dependent on the type and intensity of farm-related stress experienced by farmers. A more inclusive examination that integrates these aspects could lead to a deeper and more comprehensive understanding of the WTP model for digital agricultural extension.

This study aims to estimate the WTP for the *farmbetter* app (Figure 1, link) and to assess the factors influencing WTP among smallholder farmers in Tanzania and Burkina Faso. *Farmbetter* app (link) is a mobile phone-based digital advisory tool available since 2019 in major app stores. This app was chosen because it is currently being piloted and promoted in several countries across Asia and Africa as part of a larger project, AgriPath, which aims to enhance digital advisory services for farmers. The study enriches the literature on WTP in four significant ways. First, it explores the WTP for a new digital extension system known as *farmbetter*. It is designed to promote sustainable agriculture by providing access to over 1,000 tailored sustainable agricultural solutions, sourced from peer-reviewed WOCAT databases (link). The app uses a farmer's location to deliver context-specific knowledge and agricultural practices and is operational even in areas with low internet connectivity. The tool allows a multi-media mode of communication, encompassing text, pictures, and audio.

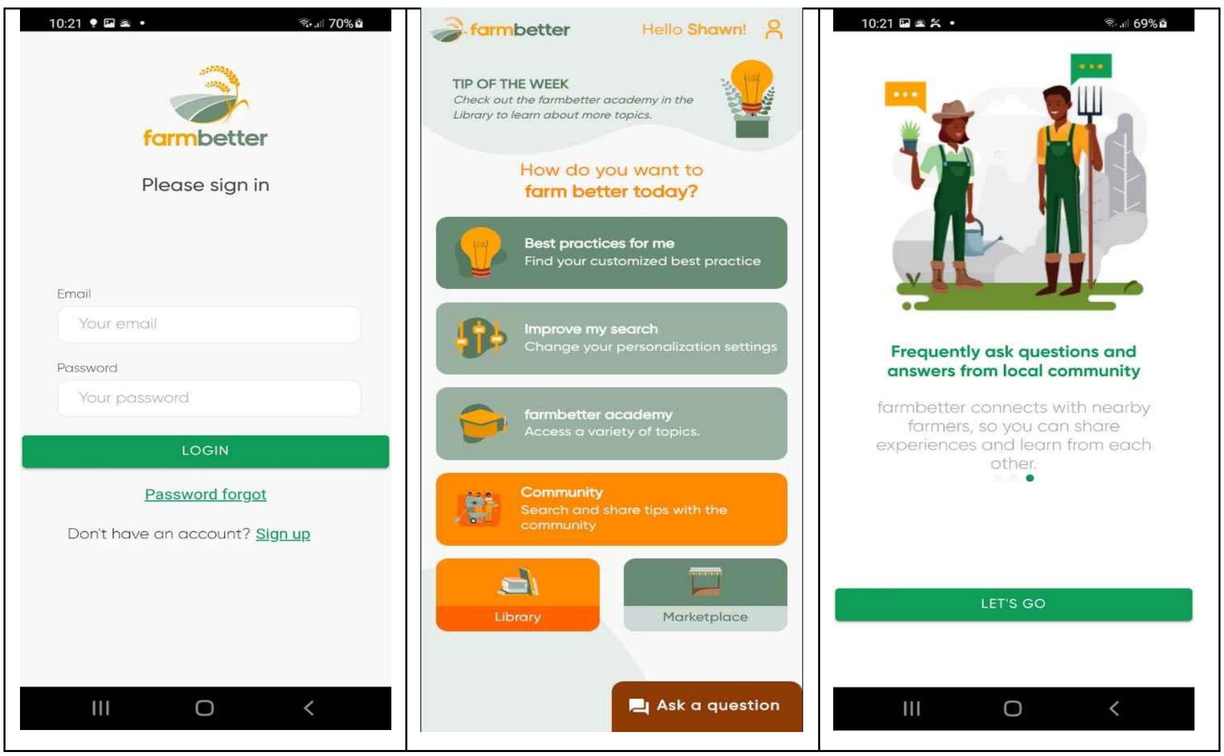

Figure 1. *farmbetter* app

Second, the study provides valuable insights into policy-relevant variables, particularly examining the influence of farmers' digital literacy and their awareness of digital extension services. Third, the study provides a cross-country analysis of WTP for a new digital extension system. Lastly, it utilizes a Least Absolute Shrinkage and Selection Operator (Lasso) regression algorithm to conduct an analysis of the determinants of WTP for the *farmbetter* app among smallholder farmers in Burkina Faso and Tanzania smallholder farmers.

2. Data and methods

2.1 Elicitation method for willingness to pay.

The contingent valuation method (CVM) is the commonly used method to elicit the respondent's WTP for goods and services that have no price directly revealed in the market (Lehberger & Grüner, 2021). This method is used to estimate the economic values of goods or services by asking hypothetical questions (Chia et al., 2020; Portney, 1994).

The most common CVMs used to elicit WTP are dichotomous choice, bidding game, payment card, and open-ended elicitation formats (Heinzen & Bridges, 2008; Javan-Noughabi et al., 2017). Both dichotomous choice and bidding game elicitation formats focus on a simple yes/no question regarding whether a respondent would pay a specified price. However, the bidding game method involves a series of yes/no questions until the maximum WTP is identified (Asioli et al., 2021; Hanemann et al., 2013; Heinzen & Bridges, 2008). On the other hand, the payment card elicitation method asks the respondents to indicate their maximum WTP from a list of prices presented in ascending order (Heinzen & Bridges, 2008). However, most of these elicitation methods produce less precise valuations (Asioli et al., 2021). To enhance precision, some studies adopt the open-ended elicitation method (Javan-Noughabi et al., 2017; Rodrigues et al., 2016; Shi et al., 2014; Wongprawmas et al., 2016). This method involves a direct question, asking respondents how much they would be willing to pay (Heinzen & Bridges, 2008). The WTP for *farmbetter* was elicited using an extended open-ended elicitation format known as the *Becker-DeGroot-Marschak* (BDM) method (Becker et al., 1964). This method provides an economic incentive to respondents to reveal their true WTP (Segal & Wang, 1993, Wertenbroch & Skiera, 2002). In the BDM method, the participant is first asked to offer a maximum bid. The bid price is recorded, after which a randomly generated offer price is drawn from a distribution of prices ranging from zero to a higher price than the bid. If the offer price exceeds the randomly generated price, the transaction takes place, if not, no transaction is aborted (Chia et al., 2020; Segal & Wang, 1993).

2.2 Experimental design

We developed a WTP experimental design based on the BDM method (Becker et al., 1964). First, each smallholder farmer was individually approached on the field and given a clear description of the *farmbetter* app, including its services and functionalities. Selected smallholder farmers were informed about the BDM mechanism procedure, by way of an example. They were also explicitly told that they could respond zero if they are not interested in the service described. Smallholder farmers were encouraged to bid honestly to help us improve our understanding of how they value the app. Second, selected farmers were asked to state their WTP for the *farmbetter* per month. Third, smallholder farmers were told that there are 15 bits of paper in the box representing random prices from TZS 1,000 to 100,000 in Tanzania and XOF 500 to 40,000 in Burkina Faso[1]. Through discussions with extension officers, the random price range was designed to cover the ranges of potential WTP values that could be expressed by the participants. Smallholder farmers were invited to randomly draw a bit of paper from some random distribution made known to the interviewer. If the stated bid was higher than the random price, smallholder farmers received nothing (Liu & Tian, 2021). However, our experiment lacked actual transactions, possibly leading to hypothetical bias (Liu & Tian, 2021, Silva et al. 2011).. To reduce this bias, we implemented the cheap talk script[2]. Evidence suggests that there is no significant difference between hypothetical values with cheap talk and actual estimates (Carlsson et al., 2005; Silva et al., 2011). Fourth, smallholder farmers were allowed to adjust their bids until they were no longer willing to make any further changes. This procedure incentivized participants to bid their true WTP.

[1] To minimize the influence of enumerators on respondents' answers, farmers were deliberately kept unaware of the different price ranges during the survey.

[2] Cheak talk contained the following messages: The experiment concerns a new mobile app designed to provide agricultural advice to farmers. We'll ask you to state the maximum amount you would be willing to pay for this app. It's important to us that you feel comfortable and confident in your responses. Remember that your responses are confidential and will only be used for research purposes. We want to emphasize that there are no right or wrong answers. The experience from previous similar surveys is that respondents often state a higher WTP than what they are truly willing to pay for a good or service. Your honest feedback is what will help us improve our understanding of how people value apps like this one. Please take your time and consider the value you place on the features and benefits of the app. Your input will play a crucial role in informing our research and potentially improving digital advisory services for farmers.

2.3 Data collection

Data used in this study were obtained from household surveys conducted in Tanzania and Burkina Faso under the Agripath project (link). Household survey data were collected between October and December 2023 using a multistage sampling scheme (Cash et al., 2022). In the first stage, the Mbarali district in the Mbeya region of Tanzania was purposively selected based on the presence of ongoing and past Kilimo Trust interventions and the production statistics of rice. Recognized as a suitable agroecological zone for rice production, Mbarali is among the top rice-producing districts in Tanzania (Mauki et al., 2023; Ngailo et al., 2016). Mbarali, a district with a population of 300,517, heavily relies on agriculture. The district is divided into 20 wards with a total of 102 villages (PO-RALG, 2022). Farmers in Mbarali have one growing season, the long season (December-June). In Burkina Faso, the provinces of *Passoré* and Zondoma were selected based on sorghum production statistics, with both provinces being recognized as top sorghum producers in the country (MASA, 2013). With populations of 459,269 and 248,495, respectively, the provinces of *Passoré* and Zondoma are subdivided into 9 and 5 departments (MEFP, 2021). Farmers in these provinces, as those in Mbarali, have a single growing season, known as the long season (June-October).

In the second stage, fifteen wards were purposively selected in the Mbarali district based on the presence of network infrastructure (Fig. 2). In Burkina Faso, the departments of Arbollé and Yako in the *Passoré* province, and the Gourcy department in the Zondoma province were purposely selected based on the presence of network infrastructure and the history of ongoing and past Solidarity and Mutual Aid in the Sahel (SEMUS) interventions (Fig. 3). In the third stage, 1 to 8 villages were randomly selected in each ward in Tanzania using the lottery method. Similarly, in Burkina Faso, 9 to 14 villages were randomly selected in each department. However, about 6 villages identified as unsafe in the target departments of Burkina Faso were replaced by secure alternatives based on community-based extension agents and SEMUS recommendations. In Tanzania, within each village, between 9 and 13 households were selected using a random start systematic sampling with a sampling interval of five households. Following the instructions provided by the research team, enumerators initiated the process by randomly selecting a household for an interview, then systematically skipped five households in any direction and interviewed the sixth household. This procedure was consistently repeated until the desired sample size was reached within each village. A similar approach was applied in Burkina Faso, where 22 to 27 households were randomly selected in each village. In total, we randomly selected a total sample of 623 farm households from 60 villages in Tanzania and 628 farm households from 27 villages in Burkina Faso.

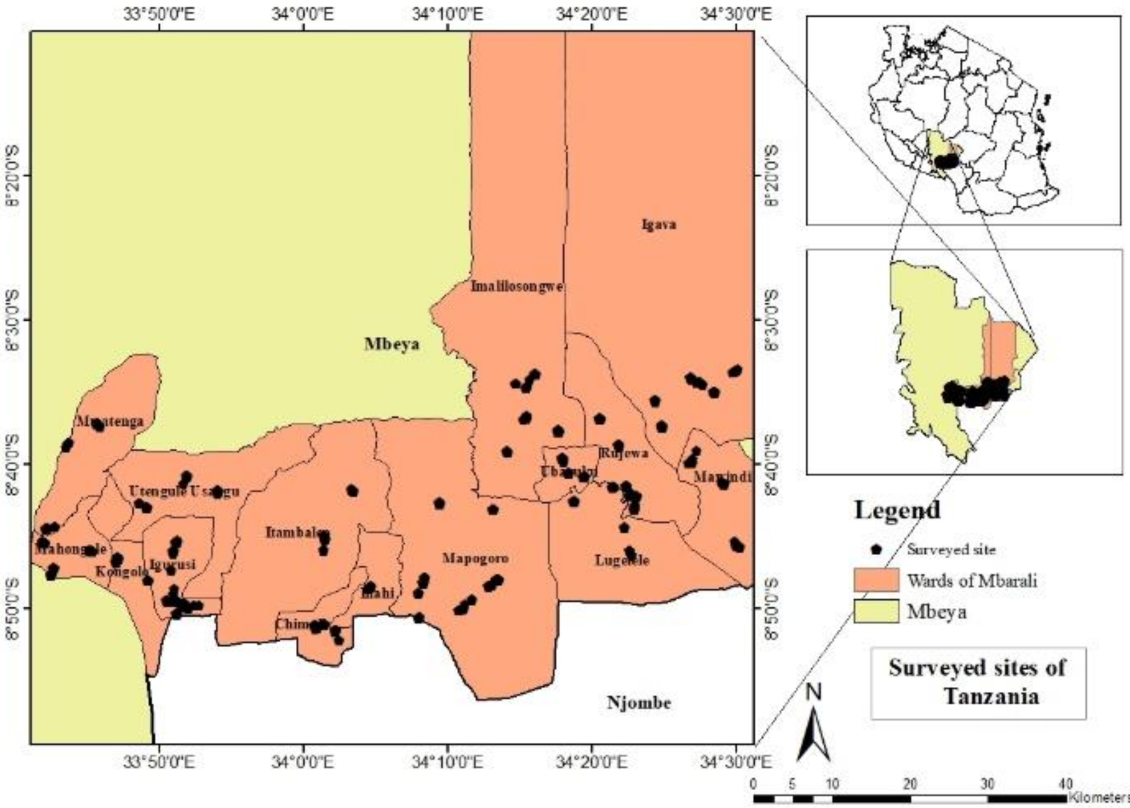

Figure 2. Study areas in Tanzania.

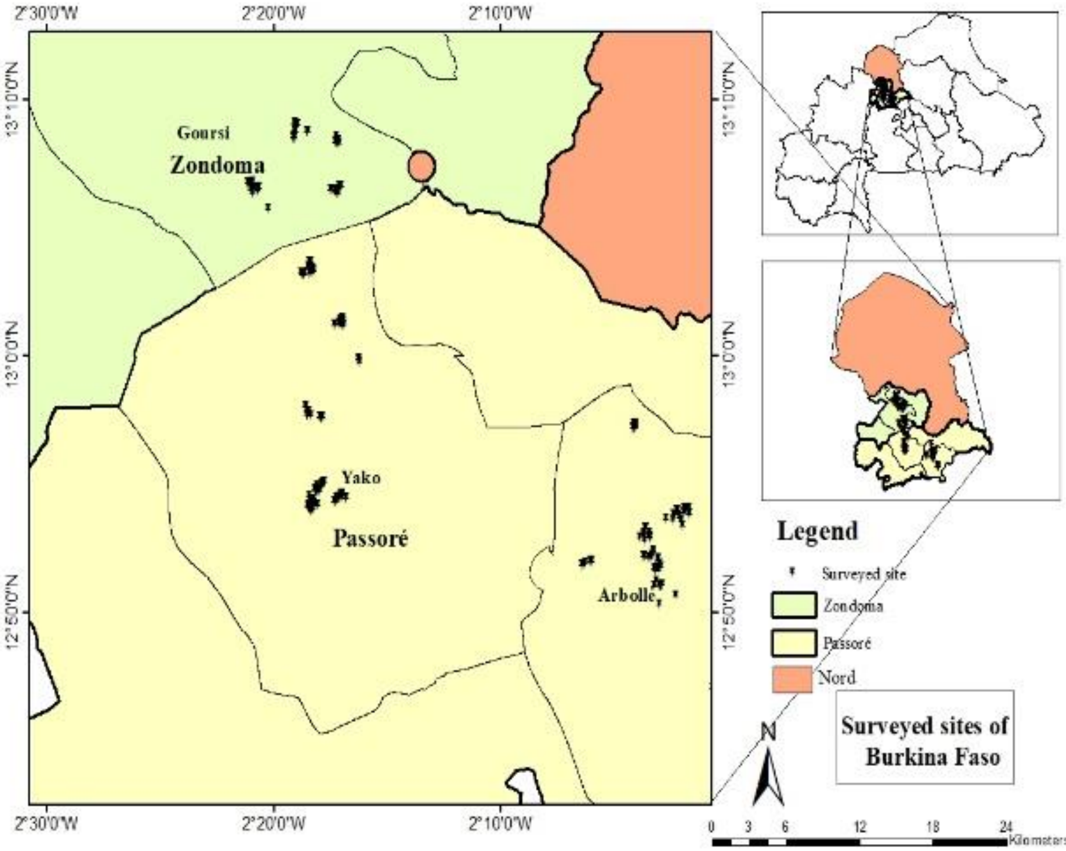

Figure 2. Study areas in Burkina Faso

Data were collected at the household and field-plot level by trained enumerators using a pretested semi-structured questionnaire that had been programmed in CSPro version 7.0. The questionnaire covered different modules including agronomic, digital extension, WTP, socio-economic, and village-level questions. Participation in the study was entirely voluntary. The verbal informed consent was obtained from each farm household.

Table 1.
Summary statistics of variables included in the estimations.

		Pooled sample (n=1251)		**Tanzania (n=623)**		**Burkina Faso (n=628)**		**Diff.**
VARIABLES	**Description**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	
Dependent variable								
WTP	Willingness to pay for *farmbetter* (USD per month)	5.44 (7.00)	2.4	4.28 (4.88)	2.4	6.65 (8.53)	2.5	-5.94***
Independent variables								
Gender of HH	Gender of household	0.27		0.29		0.25		1.53

head	head (female=1)	(0.44)		(0.46)		(0.44)		
Age of HH head	Age of household head	45.1 (11.6)	45	42.1 (11.1)	41	49.2 (10.9)	50	-11.2***
Education of HH head	Education of household head in years	5.00 (4.86)		9.00 (2.97)		1.03 (2.58)		50.71***
Household labour force	Number of household members between 16 and 65 years old.	2.91 (1.53)	2	2.31 (1.07)	2	3.51 (1.67)	3	-15.2***
Group membership	Farmer group membership (yes=1)	0.38 (0.49)		0.34 (0.47)		0.43 (0.50)		-3.21***
Extension officer visits	Farmer has received extension officer visits last year (yes=1)	0.72 (0.45)		0.67 (0.47)		0.78 (0.41)		-4.36***
SMS skills	Farmer knows how to send and receive messages on mobile phone (yes=1)	0.62 (0.49)		0.92 (0.28)		0.33 (0.47)		26.96***
Phone calling skills	Farmer knows how to make and receive phone calls (yes=1)	0.96 (0.21)		0.96 (0.20)		0.95 (0.21)		0.52
Internet skills	Farmer knows how to use the internet to search for agricultural information (yes=1)	0.18 (0.28)		0.28 (0.45)		0.08 (0.28)		9.36***
App skills	Farmer knows how to download the mobile app (yes=1)	0.10 (0.31)		0.14 (0.35)		0.07 (0.25)		4.50***
Awareness of digital extension	Farmer is aware of using mobile phones to access extension service (yes=1)	0.55 (0.50)		0.64 (0.48)		0.45 (0.49)		6.80***
Using phone calls	Farmer uses phone calls for accessing agricultural information (yes=1)	0.84 (0.37)		0.88 (0.32)		0.80 (0.40)		4.04***
Using SMS	Farmer uses text messaging for accessing agricultural information (yes=1)	0.39 (0.49)		0.71 (0.46)		0.08 (0.27)		29.88***
Using social media	Farmer uses social media for accessing agricultural information (yes=1)	0.18 (0.38)		0.21 (0.41)		0.14 (0.35)		2.96***
Checking online	Checking online for accessing agricultural information (yes=1)	0.04 (0.20)		0.05 (0.23)		0.03 (0.17)		2.30***
Mobile phone ownership	Farmer possesses a mobile phone of any kind (yes=1)	0.94 (0.24)		0.94 (0.23)		0.93 (0.25)		0.90
Smartphone ownership	Farmer possesses a smartphone (yes=1)	0.19 (0.39)		0.27 (0.45)		0.11 (0.32)		7.31***

Using radio	Farmer uses radio for accessing agricultural information (yes=1)	0.75 (0.43)		0.76 (0.43)		0.74 (0.44)		0.76
Using TV	Farmer uses TV for accessing agricultural information (yes=1)	0.35 (0.48)		0.56 (0.50)		0.14 (0.35)		17.39***
Distance to the nearest extension officer	Working time to the nearest extension officer in minutes	58.34 (46.85)	45	31.53 (30.8)	25	84.94 (44.8)	80	-24.5***
Agricultural income	Annual agricultural income (USD)	1935 (2627)	720	3443 (3075)	2646	513 (573)	378	22.55***
Pests	Farmer experiences stress related to pests/insects (yes=1)	0.13 (0.33)		0.17 (0.38)		0.08 (0.28)		4.84***
Crop diseases	Farmer experiences stress related to crop diseases (yes=1)	0.11 (0.31)		0.20 (0.40)		0.02 (0.13)		11.15***
Waterlogging	Farmer experiences stress related to waterlogging (yes=1)	0.04 (0.18)		0.03 (0.17)		0.04 (0.20)		-1.20
Drought	Farmer experiences stress related to drought (yes=1)	0.43 (0.50)		0.06 (0.23)		0.81 (0.39)		-41.1***

Note: standard deviations in the parentheses

2.3 Conceptual and econometric framework

The farmer's decision to pay or not for the *farmbetter* app will depend on the expected utility or net benefit derived from using it. The farmer's expected utility, $\mathrm{EU}_{\mathrm{d}}^{*}$, from using the *farmbetter* app is a latent variable determined by a set of observed household and farm characteristics ($\mathrm{X_i}$) and unobserved characteristics ($\mathrm{u_i}$) such that:

$$\mathrm{EU}_{\mathrm{id}}^{*} = \beta_0 + \sum_{j=1}^{p} \beta_{\mathrm{j}} \mathrm{X}_{\mathrm{ij}} + \mathrm{u_i} \qquad (\mathrm{i} = 1, \dots, \mathrm{n}) \qquad (1)$$

where $\mathrm{EU}_{\mathrm{id}}^{*}$ is the latent dependent variable, representing the level of expected utility derived from using the *farmbetter* app, i indexes individual farmer's expected utility, β_0 is the intercept, β_i is the regression coefficient, X is a vector of covariates that influence farmers' WTP, u_i is an error term, which assumes a normal distribution. Farmer i may decide to pay a given amount of money for the *farmbetter* app if the expected utility (net benefit) from using it, $\mathrm{EU}_{\mathrm{d}}^{*}$, is greater than not using it, $\mathrm{EU_0}$. The equation that describes the observable decision of farmers can be specified as follows:

$$\mathrm{WTP_i} > 0 \text{ if } \mathrm{EU_d^*} - \mathrm{EU_0} > 0 \tag{2}$$

The selection of explanatory variables included in the econometric models (Table 1) was based on previous studies on WTP for extension service (Abebe, 2023; Abed et al., 2020; Ajayi, 2006; Badr, 2019; Bonke et al., 2018; Gosbert et al., 2019; Hidrobo et al., 2022; Sumo et al., 2023; Ulimwengu & Sanyal., 2011).

Tobit estimation models are typically used to assess WTP data obtained through the BDM elicitation method (Asioli et al., 2021; Ngoma et al., 2023). The rationale behind this methodological choice lies in the BDM method's ability to generate continuous valuations, including zero values. Therefore, using ordinary least squares (OLS) models could potentially lead to biased and inefficient estimates when the number of zeros in the dependent variable is large (Wilson & Tisdell, 2002). The number of zeros in our outcome variable is about 20% of the total observations, hence, relying on OLS regression for accurately estimating the farmer's WTP for digital extension might be inadequate. This is because some predictors —including mobile phone ownership, digital literacy skills, use of digital agricultural advisory services, crop diseases, pests, etc.— are highly correlated (Wang et al., 2018). The Least Absolute Shrinkage and Selection Operator (Lasso) machine learning algorithm addresses the limitations of OLS, including over-fitting problems and limitations in dealing with multicollinearity (Tibshirani, 1996; Ranstam & Cook, 2018). Therefore, the Lasso machine learning algorithm was applied in this study to deal with multicollinearity problems and select the reliable predictors of the farmer's WTP for digital extension (e.g., Hidrobo et al. 2022). The Lasso machine learning algorithm entails the introduction of a regularization parameter (λ) in the standard linear regression, which effectively shrinks some predictors toward zero. The Lasso machine learning tries to minimize the following objective function (Tibshirani, 1996):

$$\left(\sum_{i=1}^{n} \mathrm{WTP_i} - \beta_0 - \sum_{j=1}^{p} \beta_j \mathrm{X_{ij}}\right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{3}$$

where n is the sample size and p the number of covariates. The parameter $\lambda \geqslant 0$ controls the amount of regularization that is applied to covariates. If λ is large, all the covariates are almost zero, and if λ has smaller values, the Lasso shrinks some of the estimated covariates equal to zero. By adding λ to the standard linear model, the Lasso machine learning algorithm improves the model's prediction accuracy and prevents overfitting (Ranstam & Cook, 2018). Following Wang et al. (2018), the study adopts a 10-fold cross-validation approach to estimate the optimal λ. This method involves splitting the original dataset into training and testing datasets. In line with Afendras and Markatou (2019), we used half of the original dataset as our training sample size to ensure robust evaluation. The Kernel density plot in Fig. 4 indicates that both training and testing datasets share similar distributions, indicating a balanced split and reinforcing the validity of our cross-validation approach.

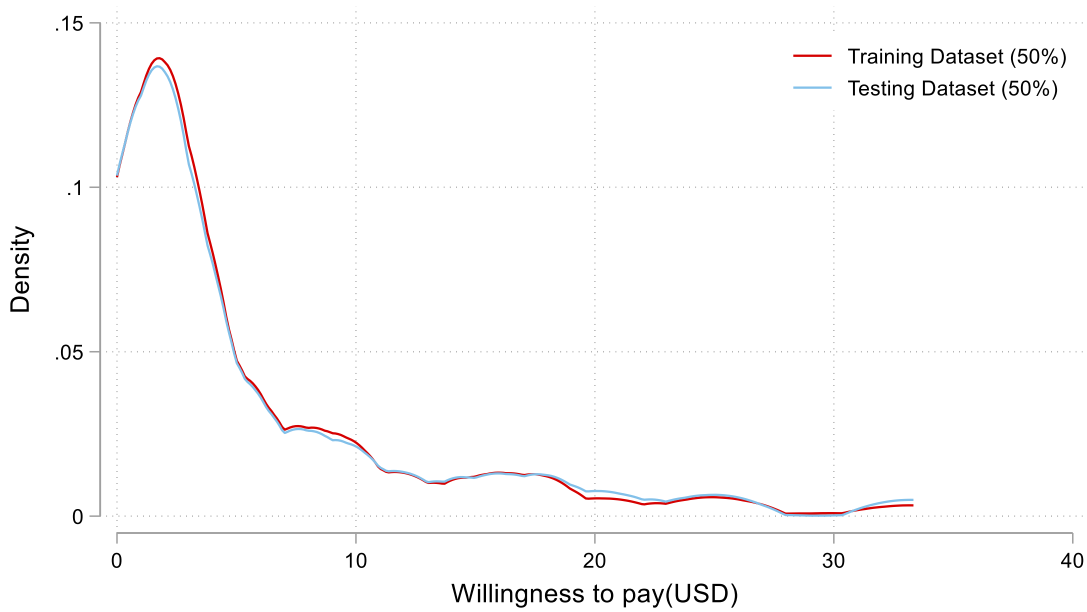

Figure 4. Kernel density plot of WTP.

The model of the farmer's WTP was predicted using the training dataset and the optimal model was obtained by calculating the best parameter, λ, corresponding to the minimum mean squared error (MSE). The value of λ was estimated using cross-validation, Minimum BIC, and adaptive lasso selection methods. Table 2 shows that Cross-validation and Adaptive Lasso selected more variables than the Minimum BIC Lasso. This indicates that the Minimum BIC Lasso provides a more parsimonious regularization, selecting 11 out of the 26 covariates.

Table 2.
Results of the variable selection in the regularization of the WTP model

Variable	Cross-validation	Minimum BIC	Adaptative
Drought	x	x	x
Using radio	x	x	x
Using SMS	x	x	x
Group membership	x	x	x

Smartphone ownership	x	x	x
Waterlogging	x	x	x
Using phone calls	x	x	x
HH Labour force	x	x	x
SMS skills	x	x	x
Traditional Extension	x	x	x
Agricultural income	x		x
Internet skills	x		x
Age of HH head	x		x
Pests	x		x
Gender of HH head	x	x	
App skills	x		
Constant	x	x	x

The sign "x" shows which covariates were selected from the Lasso technique.

To determine which Lasso estimator performed better for out-of-sample prediction, we reported the Mean Squared Error (MSE) and R-squared as the performance measures. A lower MSE and a higher R-squared value indicate a better fit for the model (Yang et al., 2018). As can be seen from Table 3, the Minimum BIC Lasso selection model emerged as the best model providing the lowest MSE value and the highest R-squared. Therefore, the best λ minimizing the cross-validation function is λ= 0.3859 (Figure A.1 Appendix A) and the Minimum BIC Lasso selection model is the preferred choice for inference.

Table 3.
Out-of-sample prediction results

Technique	Sample	MSE	R-squared	Observations
Cross-validation	Training	34.784	0.250	515
	Testing	51.747	0.077	513
Minimum BIC	Training	36.134	0.211	598
	Testing	47.515	0.091	601
Adaptative	Training	34.804	0.250	515
	Testing	51.919	0.074	513

Next, we applied the cross-fit partialing out Lasso regression also known as double machine learning to estimate the marginal effects of the selected predictors, while treating location-fixed effects as controls. This approach is widely recognized as the best solution, surpassing both double selection and partialing-out techniques, even though it can require a longer computational runtime (Cameron & Trivedi, 2022). The cross-fit partialing out Lasso regression uses regularized regression techniques and cross-fitting to construct the estimator (Jung et al., 2021). The accuracy of this model was assessed through 10 resamples. Observations above the 95th percentile were considered potential outliers. The results are presented in Table 4.

3. Results and discussion

3.1. Descriptive statistics

A total of 1,251 households participated in this study, with 623 from Tanzania and 628 from Burkina Faso. Table 1 shows that 29% in Tanzania and 25% in Burkina Faso were female-headed households. On average, household heads were 42.1 years in Tanzania, compared to 49.2 in Burkina Faso. Tanzania farmers had 9 years of formal schooling, compared to just 1 year for their counterparts in Burkina Faso. The average number of adults in the households surveyed was 2.3 in Tanzania and 3.5 in Burkina Faso. Around 34% of farmers in Tanzania, compared to 43% in Burkina Faso, were members of community-based associations. During the 2022/23 growing season, 67% of farmers received extension officer visits in Tanzania, compared to 78% in Burkina Faso. The mean walking time to the nearest extension officer was 31.5 minutes in Tanzania and 44.8 minutes in Burkina Faso.

Around 64% of farmers in Tanzania, compared to 45% in Burkina Faso, were aware that mobile phones can be used to access agricultural information. Regarding digital literacy, a significant gap existed among Tanzania and Burkina Faso farmers. At least 92% of farmers in Tanzania, compared to 33% in Burkina Faso, could send and receive text messages. The majority of farmers were able to make and receive phone calls: 96% in Tanzania and 95% in Burkina Faso. However, the technical skills needed to download mobile apps were limited in both countries. Only 14% of farmers in Tanzania and 7% in Burkina Faso were able to download mobile apps. About 28% of farmers in Tanzania, compared to 8% in Burkina Faso, could search for information on the internet. Consequently, the actual usage remains low. About 5% of farmers in Tanzania and 3% in Burkina Faso used the Internet for accessing agricultural information. At least 21% of farmers in Tanzania, compared to 14% in Burkina Faso, used social media for accessing agricultural information. Regarding the use of other digital agricultural advisory services (DAAS), 88% of farmers in Tanzania and 80% in Burkina Faso used phone calls to access agricultural information. In addition, 71% of farmers in Tanzania, compared to 8% in Burkina Faso, used text messages. Radio was another prevalent source of agricultural information in both countries. At least 76% of farmers in Tanzania and 74% in Burkina Faso used radio to access agricultural information. However, TV was commonly used in Tanzania (56%) compared to Burkina Faso (14%).

In terms of mobile phone ownership, Table 1 shows that 94% of farmers in Tanzania and

93% in Burkina Faso owned a mobile phone. However, only 24% of farmers in Tanzania and 11% in Burkina Faso, possessed smartphones. Regarding farm income, farm households surveyed earned USD 3,443 in Tanzania and USD 513 in Burkina Faso during the 2022/23 growing season. Farmers reported various challenges: 17% of farmers in Tanzania and 8% in Burkina Faso reported pest stress, 20% in Tanzania and 2% in Burkina Faso reported crop diseases, 3% in Tanzania and 4% in Burkina Faso reported waterlogging stress, and 6% in Tanzania and 81% in Burkina Faso reported droughts.

3.2. Willingness to pay for the *farmbetter* app.

3.1.1. Farm-related stress, access to extension service, group membership, and WTP.

The findings from the study as shown in Table 1 indicated that smallholder farmers, on average, were willing to pay USD 5.4 monthly for the *farmbetter* app, with a median of USD 2.4. Specifically, farmers in Burkina Faso were significantly willing to pay more (USD 6.7), with a median of USD 2.5, than those in Tanzania (USD 4.3) who averaged USD 4.3, with a median of USD 2.4. This can be attributed to the semi-arid climate experienced in Burkina Faso, which probably increases the demand among farmers for effective advisory and extension services to enhance their resilience in such challenging climate conditions (USAID, 2017). Unsurprisingly, smallholder farmers who reported farm stresses in both countries were willing to pay more than their counterparts who did not, suggesting that farm-related stress is associated with increased demand for (digital) extension services (Atube et al., 2021). In Tanzania, farmers who reported pests and crop diseases were willing to pay more compared to those who did not. Similarly, in Burkina Faso, farmers facing waterlogging and drought-related stresses showed a significantly higher WTP compared to their counterparts who did not. However, farmers who reported pests in Burkina Faso were significantly willing to pay less than those who did not (Fig. 5).

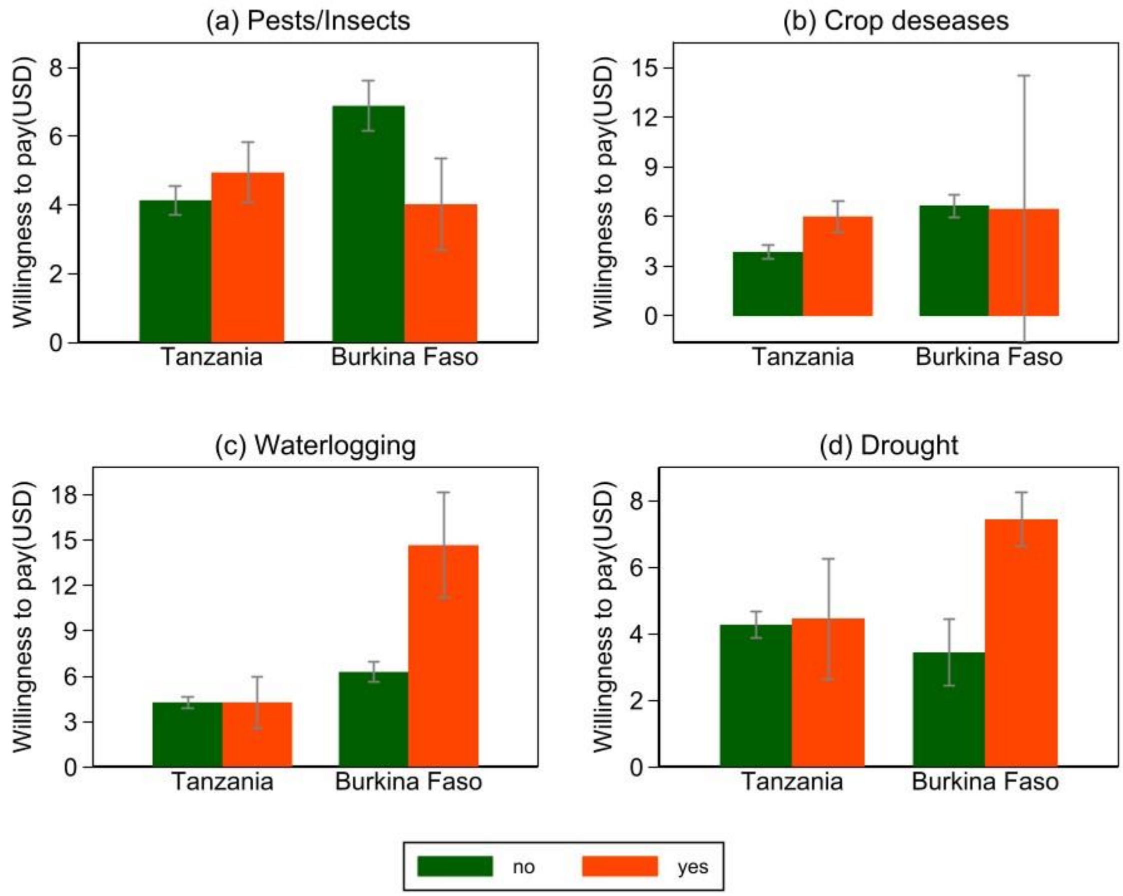

Figure 5. Farm-related stress and WTP for the *farmbetter* app.

In Tanzania, farmers who had access to extension were willing to pay more for the *farmbetter* app than those who did not (Fig. 6). However, in Burkina Faso, farmers who did not access to extension were significantly willing to pay more than those who had, suggesting a need for their inclusion into the extension system. Moreover, farmers who were members of farmers' organizations showed a higher WTP compared to their non-member counterparts, with significant differences observed particularly in Burkina Faso. This could be a result of both peer effects in terms of pressure to access digital extension and also learning to value extension advice through their friends (Xiong et al., 2016).

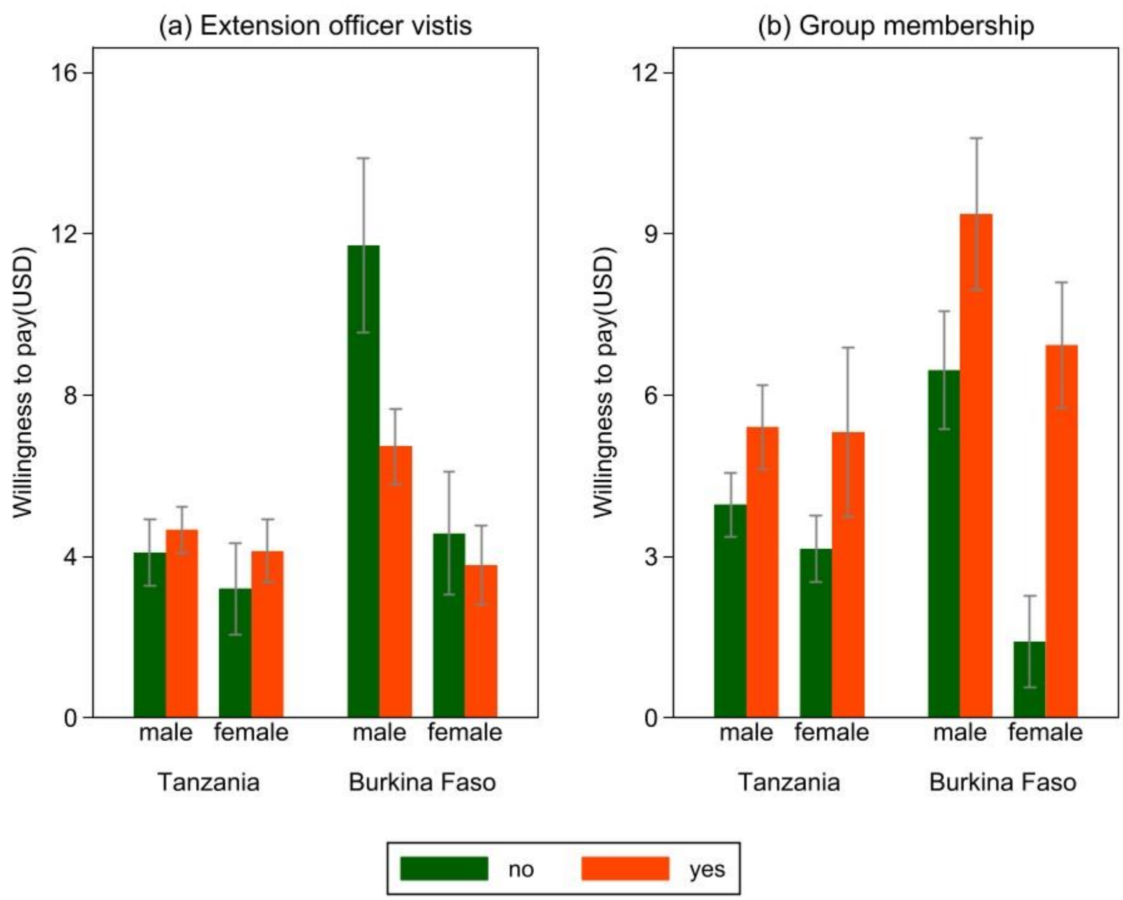

Figure 6. Extension officer visits, group membership, gender, and WTP for the *farmbetter* app.

Gender differences in WTP were observed among household heads. Fig. 6 shows that female-headed households who received extension officer visits or those who were members of farmers' groups were willing to pay less than their male counterparts. However, overlapping confidence intervals (CIs) suggest no significant difference in Tanzania.

3.1.2. Digital literacy skills, experience with digital agricultural advisory services (DAAS), and WTP.

In Figure 7, we show the WTP by digital literacy aspects. Overall, smallholder farmers with digital literacy skills were willing to pay more for the *farmbetter* app than their counterparts who did not have such skills, suggesting the crucial role of digital skills in driving the demand for digital extension services (McCampbell et al., 2021). In Tanzania, smallholder farmers who could send and receive text messages, make and receive phone calls, use the internet, and download mobile apps showed a higher WTP for the *farmbetter* compared to those without these essential skills. However, significant differences in WTP were only observed among farmers who could send and receive SMS and download mobile apps versus those who could not. Smallholders who could send and receive SMS were willing to pay about USD 2.5 more than those who could not, while those who could download mobile apps were willing to pay roughly USD 1.7 more than their counterparts who could not (Fig. 7). In Burkina Faso, a significant difference was only observed between farmers who could send and receive SMS and those could not. Specifically, farmers who could send and receive SMS were willing to pay USD 2.7 compared to those without such skills.

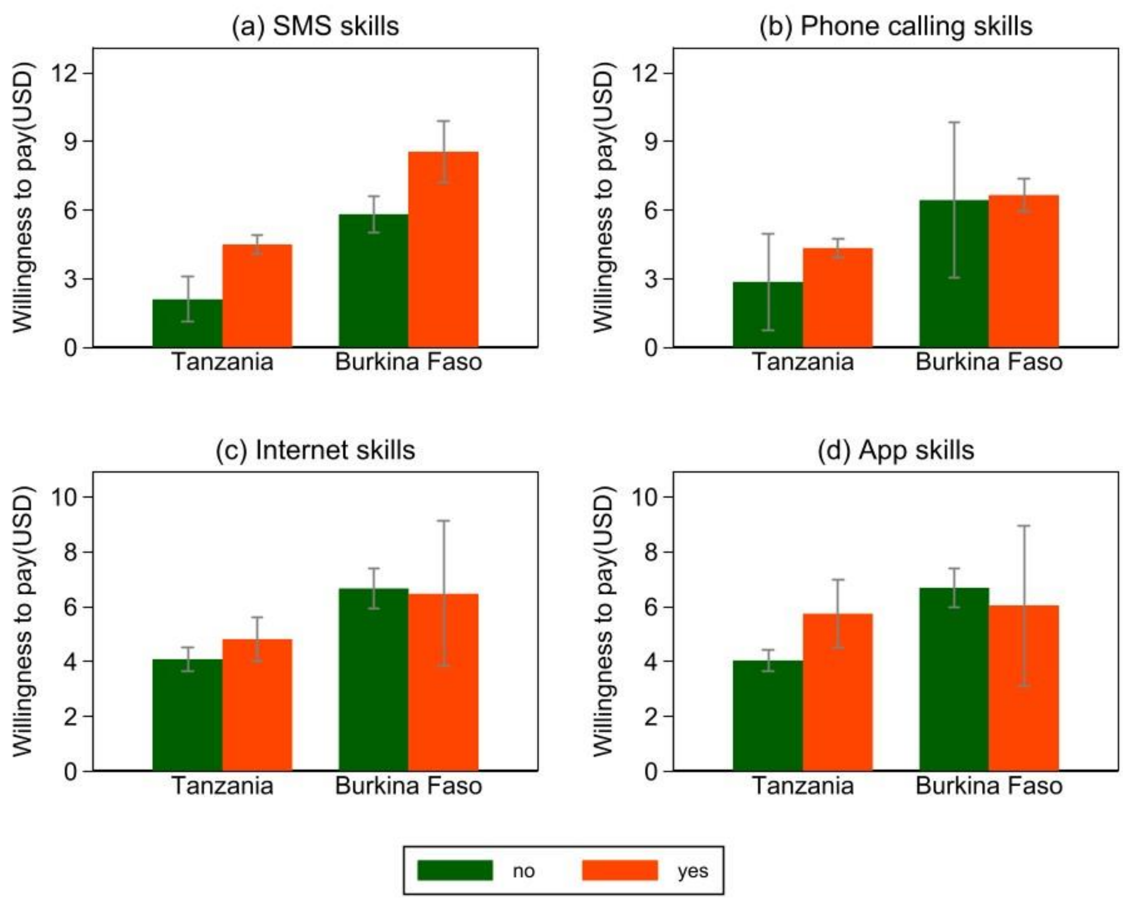

Figure 7. Digital literacy skills and WTP for the *farmbetter* app.

Regarding DAAS, Fig. 8 shows that farmers who used digital channels to access agricultural advisory and extension services had a higher WTP for the farmbetter compared to those who did not leverage such tools. In Tanzania, farmers using social media platforms, search engines, radio, and TV were willing to pay around USD 0.6, USD 2.5, USD 1.6, and USD 1.1 more, respectively, than their counterparts who did not use such communication methods. However, farmers who used SMS and phone calls showed a lower WTP compared to their counterparts who did not. However, significant differences in WTP were observed only among farmers who used search engines and radio versus those who did not. In Burkina Faso, farmers who used SMS, phone calls, social media, radio, and TV showed a higher WTP compared to their counterparts who did not. However, significant differences in WTP were observed only among farmers who used phone calls or radio and those who did not. Precisely, farmers who used phone calls and radio were willing to pay USD 5.2 and USD 3.7 more, respectively, than those who did not.

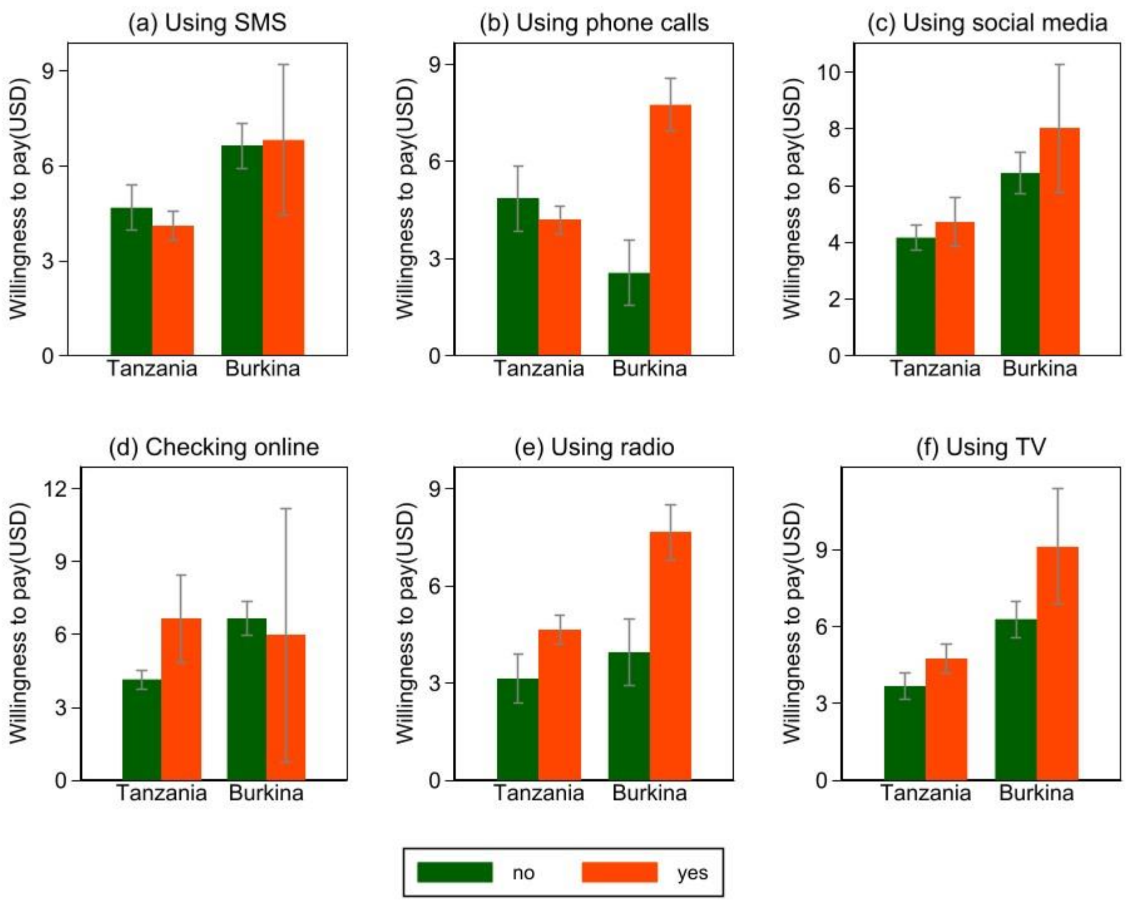

Figure 8. Use of digital advisory services and WTP for the farmbetter app.

The demand curve is downward sloping from left to right as expected (Fig. 9), implying that the proportion of smallholder farmers willing to pay for the *farmbetter* app decreases as the payment amount increases in the pooled sample, Tanzania, and Burkina Faso. The horizontal line is the average WTP for the *farmbetter* app.

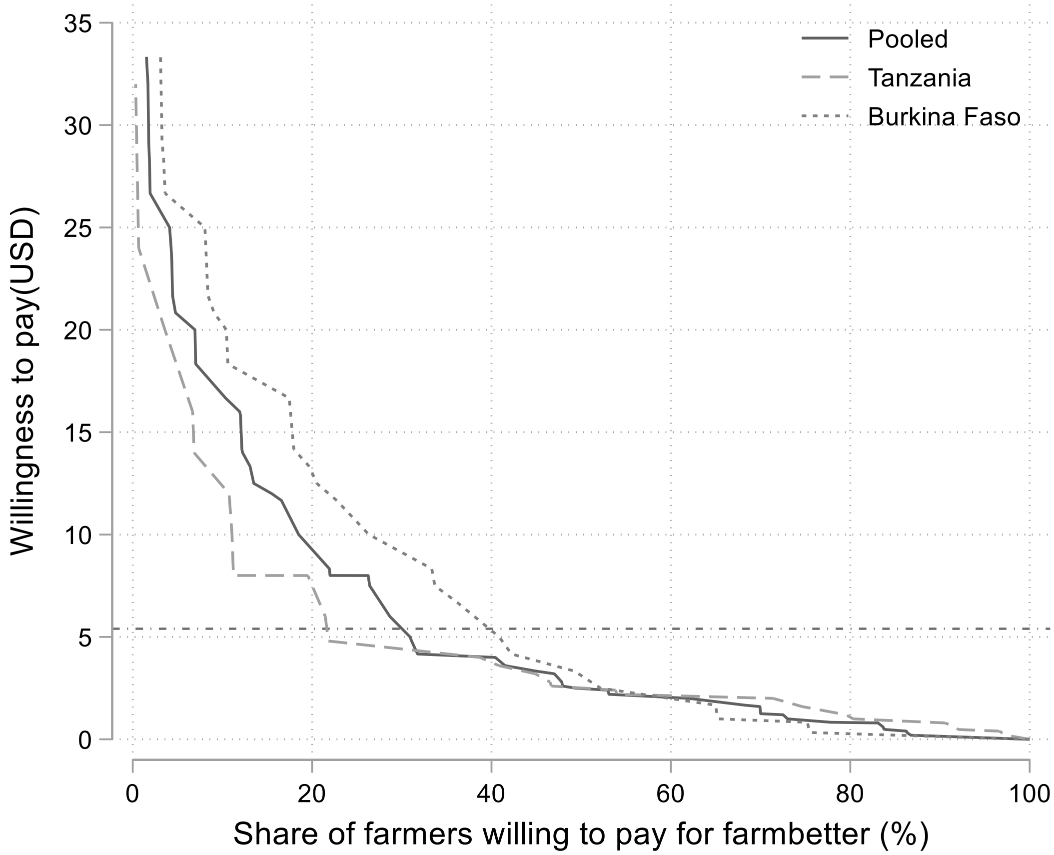

Figure 9. Demand curves for the farmbetter app in Tanzania and Burkina Faso

3.3 Factors influencing smallholder farmers' willingness to pay (WTP) for the *farmbetter* app.

The determinants of smallholder farmers' WTP for the *farmbetter* app are presented in Table 4. Columns 1-2 present OLS and Lasso estimates from the pooled sample. In columns 3-4, OLS and Lasso estimates for Tanzania are provided, while columns 5-6 present OLS and Lasso estimates for Burkina Faso. This study relied on Lasso estimates, which are more robust than OLS estimates (Tibshirani, 1996). The Lasso results revealed that female-headed households were significantly less willing to pay for the farmbetter app (except in Tanzania where the coefficient was not statistically significant but still negative), probably due to their typically limited financial resources and risk-averse attitudes (Filippin, 2022). Another possible explanation for this can be attributed to the digital literacy gender gap, which can diminish women's interest and demand for digital agricultural and advisory services (Subrahmanian et al., 2022). This result implies a lower demand among female farmers for extension services. This aligns with prior research that confirms the persistence of gender gaps in access to extension services in West Africa (Medagbe, 2023, Miine et al., 2023). Households with more adults were significantly more willing to pay for farmbetter in Tanzania and Burkina Faso, indicating the importance of household labour availability in driving the demand for digital extension services.

Table 4.
Factors influencing willingness to pay for the *farmbetter* app in Tanzania and Burkina Faso

	Pooled sample		Tanzania		Burkina Faso	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	OLS	Lasso	OLS	Lasso	OLS	Lasso
Gender of HH head (1=Female)	-1.101**	-1.327***	0.227	-0.252	-1.674**	-2.1109***
	(0.429)	(0.379)	(0.540)	(0.425)	(0.696)	(0.6006)
Age of HH head (years)	-0.028		-0.005		-0.060**	
	(0.022)		(0.023)		(0.028)	
Education of HH head	-0.042		0.091		-0.061	
	(0.093)		(0.084)		(0.145)	
Household labour force	0.184	0.230	0.162	0.401*	0.181	0.3706*
	(0.209)	(0.173)	(0.245)	(0.223)	(0.218)	(0.2033)
Group membership	0.925*	1.298***	1.708***	1.115**	-0.576	-1.0021
	(0.524)	(0.430)	(0.606)	(0.511)	(0.712)	(0.7551)
Extension officer visits	-1.449***	-1.297***	-0.318	0.324	-1.357	-0.8515
	(0.446)	(0.413)	(0.602)	(0.442)	(0.826)	(0.6970)
Distance to extension officer	-0.008		0.015*		-0.004	
	(0.008)		(0.009)		(0.008)	
SMS skills	1.942***	1.581***	2.024**	1.851***	-0.501	0.0702
	(0.704)	(0.591)	(0.785)	(0.594)	(0.776)	(0.8167)
Phone calling skills	-0.992		-0.748		-2.537*	
	(1.235)		(1.372)		(1.313)	
Internet skills	-0.736		-0.092		-0.826	
	(0.663)		(0.733)		(0.944)	
App skills	-0.188		0.294		1.541	
	(1.001)		(1.038)		(1.377)	
Awareness of digital extension	0.835*		0.020		1.513**	
	(0.478)		(0.436)		(0.759)	
Using phone calls	2.813***	2.649***	0.482	-0.205	1.157	1.5966
	(0.588)	(0.537)	(0.718)	(0.753)	(0.951)	(1.2212)
Using SMS	-2.192***	-2.172***	-1.853***	-0.912*	-1.343	-0.2493
	(0.574)	(0.494)	(0.596)	(0.547)	(1.307)	(1.0948)
Using social media	-1.117		-1.941**		1.825	
	(0.907)		(0.790)		(1.366)	
Checking online	-0.260		1.451		-4.517*	
	(1.488)		(1.686)		(2.555)	
Using radio	1.443***	1.656***	0.295	1.121**	1.938***	1.9375***
	(0.516)	(0.434)	(0.518)	(0.472)	(0.720)	(0.7379)
Using TV	0.365		0.379		0.644	
	(0.513)		(0.483)		(0.976)	
Mobile phone ownership	1.102		0.690		-0.447	
	(0.745)		(0.876)		(0.810)	
Smartphone ownership	2.299***	1.697***	1.630*	1.298**	2.273	2.6962**
	(0.853)	(0.579)	(0.871)	(0.510)	(1.456)	(1.3773)
Ln (agricultural income)	0.405**		0.665***		1.409**	

	(0.205)		(0.210)		(0.571)	
Pests stress	-2.023***		-1.857**		-1.153	
	(0.565)		(0.911)		(1.077)	
Crop diseases	2.468***		2.015**		6.221	
	(0.823)		(0.839)		(4.972)	
Waterlogging	3.030**	3.616***	-1.233	-0.804	-0.662	-0.4567
	(1.344)	(1.178)	(0.917)	(0.833)	(2.159)	(1.7097)
Drought stress	3.868***	2.951***	-0.538	-0.682	-0.335	-0.2040
	(0.707)	(0.594)	(1.136)	(0.984)	(1.064)	(0.8250)
Constant	-1.785		-2.739		-2.752	
	(2.371)		(2.835)		(3.932)	
Observations	1,028	1,199	526	615	502	584
F & Wald ch2(11)	7.56***	171.57***	3.22***	79.13***	14.48***	57.03***
In-sample RMSE	36.37	36.13				
Out-of-sample RMSE	47.78	47.52				
Number of folds in cross-fit	1	10		10		10
Number of resamples	1	10		10		10
Location fixed effect	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Farmers who participated in farmer organizations were significantly willing to pay more in the pooled sample and Tanzania. This is because participation in farmer organizations can lead to increased farmers' perceived value, awareness, and use of digital agricultural technologies, thereby increasing the WTP (Hoang & Tran, 2023; Miine et al., 2023). Similar results have been documented in Kenya, indicating that participation in CBOs leads to a significant increase in demand for extension services (Gido et al., 2015). However, farmers who received extension officer visits were significantly willing to pay less in the pooled sample. This could be attributed to the common practice in most developing countries, where farmers receive extension officer visits at no cost (Sylla et al., 2019; Ozor et al., 2011). The costs associated with these visits are typically covered by government subsidies and support from international organizations (Agwu et al., 2023; Sylla et al., 2019). However, a study conducted in Nigeria by Amoussohoui (2023) on the adoption of the RiceAdice application revealed a mixed effect of contact with extension officers. Amoussohoui (2023) explained this by referring to a level of uncertainty regarding the understanding of the technology. In terms of digital literacy skills, farmers who possessed SMS skills were significantly willing to pay more for the farmbetter app, possibly because digital skills are a crucial prerequisite for both the use and demand for digital agricultural technologies (FAO 2023). Previous studies highlight that farmers' limited e-literacy and digital skills are a common constraint affecting the demand for digital agricultural technologies in developing countries (Abdulai et al., 2023; Coggins et al., 2022; FAO 2023; Kansiime et al., 2022; McCampbell et al., 2021). WTP for the *farmbetter* also varied for the different digital tool types. The use of text messages significantly and negatively influenced WTP, whereas the use of search engines and radio significantly and positively influenced WTP. A probable explanation for this is that relying on an SMS-based extension might limit the amount of information that can be needed before adopting a new extension platform (Fabregas, Kremer, Lowes, et al., 2019). However, ownership of a smartphone significantly and positively influenced WTP. This aligns with previous findings in sub-Saharan Africa. For instance, Abebe (2023), using double-bound elicitation and Tobit analysis, found that farmers who owned mobile phones showed a higher WTP for mobile-based extension service than those without mobile phones. Regarding farm-related stress, stress related to waterlogging and drought significantly and positively influenced WTP. This might be attributed to the farmers' intensive quest for information to enhance their resilience and adaptability in coping with farm stresses, waterlogging and drought included (Abed et al., 2020).

Although the study is primarily based on Lasso estimates, we found additional relevant explanatory variables from OLS models. Specifically, OLS estimates showed that the distance to the nearest extension officer significantly and positively influenced WTP in Tanzania, probably because digital extension helps overcome informational barriers [e.g., travel distances, road conditions, transaction costs, etc.] (Agnihotri et al., 2023; Cole & Fernando, 2021; Fabregas, Kremer, & Schilbach, 2019). This is logical because farmers' demand for traditional agricultural extension decreases as the distance to the extension officer increases (Gido et al., 2015; Lee et al., 2023; Sumo et al., 2023). As Cole and Fernando (2023) indicated, digital extension enables to deliver timely, relevant, and actionable extension advice to farmers, especially those in remote areas, at a much lower cost. Similarly, farmers who reported that they are aware of the digital extension were significantly more willing to pay for farmbetter in the pooled sample and Burkina Faso. This might be attributed to their recognition of the benefits associated with leveraging digital agricultural technologies that are available in the region. Moreover, farm income significantly and positively influenced WTP. This aligns with previous findings in sub-Saharan Africa which also documented the positive relationship between income and WTP for extension services (Abed et al., 2020; Ajayi, 2006; Cole & Fernando, 2021; Gosbert et al., 2019; Sumo et al., 2023). Furthermore, farmers who reported crop diseases were significantly more willing to pay for the farmbetter app in the pooled sample. This suggests that when faced with challenges such as crop diseases, farmers tend to seek more support and information (Ristaino et al., 2021), thereby increasing their demand for extension services. Through a study in Kenya and Uganda, Kansiime et al. (2022) reported that the most common knowledge gap concerns pest and disease control. Interestingly, a recent study in Tanzania revealed that farmers have the highest WTP for integrated pest management extension services (Abed et al., 2020). The results of this study imply that policies and programs aimed at promoting digital extension can ensure access to smartphones, improve digital skills, and promote participation in CBOs because increasing access to smartphones, improving digital competencies, and enhancing participation in CBOs could significantly improve demand for digital extension among farmers.

Conclusion

Assessing farmers' WTP for extension services is crucial for understanding the financial sustainability of extension services that support farmers' livelihoods. Several studies document farmers' WTP for traditional extension services but few look at the WTP for digital extension. In this study, we first analysed the WTP for a new digital extension platform called the *farmbetter* app; next, we estimated the factors influencing WTP using a farm-household survey in Tanzania. We used the BDM method to elicit WTP and cross-fit partialing Lasso regression to estimate the factors influencing WTP. The funding revealed a WTP for the *farmbetter* app among farmers, averaging around USD 5.4 per month. Interestingly, Burkina Faso farmers showed a significantly higher WTP compared to their counterparts in Tanzania. This study also showed that several variables shape farmers' WTP. The WTP was observed to increase as the distance to the nearest extension officer and the farmers' agricultural income increased and with farmers' skills in mobile apps. Another major finding was that the gender of the household, participation in farmer organizations, contact with extension officers, the household's access to smartphones, the use of digital tools, and experiences with farm-related stress were important factors influencing farmers' decisions to pay for the *farmbetter* app. This study presented evidence that supports the introduction of charges for digital agricultural services to engage farmers in financing agricultural extension. Another significant implication is that effective policy measures to promote digital extension should include the improvement of household levels of digital literacy skills and rural households' access to mobile phones.

Acknowledgments

The authors gratefully acknowledge the financial support for this research by the following organizations and agencies: the Swiss Agency for Development and Cooperation (SDC); (AgriPath project), contract number 81068366; the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH agreement number 81275789; the Swedish International Development Cooperation Agency (Sida); the Swiss Agency for Development and Cooperation (SDC); the Australian Centre for International Agricultural Research (ACIAR); the Norwegian Agency for Development Cooperation (Norad); the Federal Democratic Republic of Ethiopia; and the Government of the Republic of Kenya. The views expressed herein do not necessarily reflect the official opinion of the donors.

Appendix A

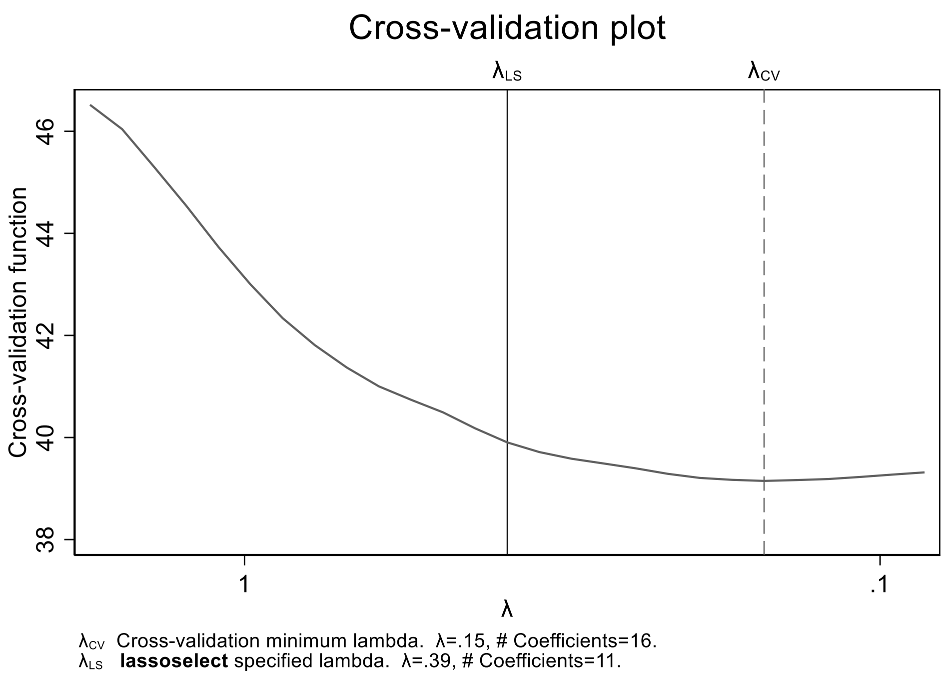

Figure A1. Cross-validation function

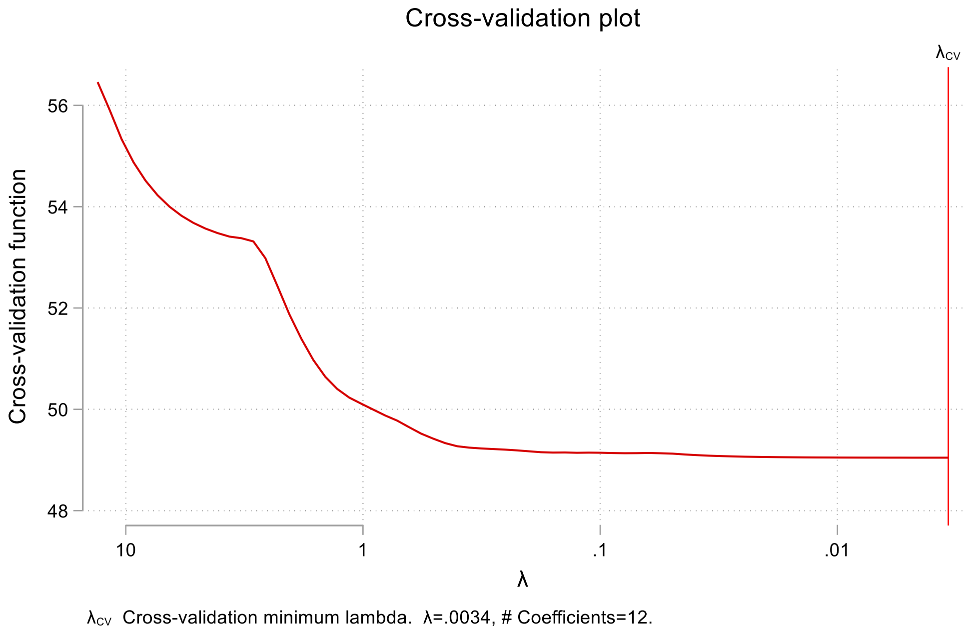

Figure A2. Cross-validation function-based adaptative Lasso technique

References

Abdulai, A. R., Tetteh Quarshie, P., Duncan, E., & Fraser, E. (2023). Is agricultural digitization a reality among smallholder farmers in Africa? Unpacking farmers' lived realities of engagement with digital tools and services in rural Northern Ghana. *Agriculture and Food Security*, *12*(1), 1–14. https://doi.org/10.1186/s40066-023-00416-6

Abebe, A. (2023). Farmers' willingness to pay for mobile phone-based agricultural extension service in northern Ethiopia. *Cogent Food and Agriculture*, *9*(1). https://doi.org/10.1080/23311932.2023.2260605

Abed, R., Sseguya, H., Flock, J., Mruma, S., & Mwango, H. (2020). An evolving agricultural extension model for lasting impact: How willing are tanzanian farmers to pay for extension services? *Sustainability*, *12*(20), 1–13. https://doi.org/10.3390/su12208473

Afendras, G., & Markatou, M. (2019). Optimality of training/test size and resampling effectiveness in cross-validation. *Journal of Statistical Planning and Inference*, *199*, 286–301. https://doi.org/10.1016/j.jspi.2018.07.005

Agnihotri, A., Madon, T., & Gadgil, A. J. (2023). Introduction to Development Engineering. In *Introduction to Development Engineering*. https://doi.org/10.1007/978-3-030-86065-3_1

Agwu, A.E., Suvedi, M., Chanza, C., Davis, K., Oywaya- Nkurumwa, A., Najjingo Mangheni, M., and Sasidhar, P.V.K. (2023). Agricultural Extension and Advisory Services in Nigeria, Malawi, South Africa, Uganda, and Kenya. Partnerships for Innovative Research in Africa (PIRA) Research Report. East Lansing, Michigan, USA: Alliance for African Partnership, Michigan State University.

Ajayi, A. O. (2006). An Assessment of Farmers' Willingness to Pay for Extension Services Using the Contingent Valuation Method (CVM): The Case of Oyo State, Nigeria. *The Journal of Agricultural Education and Extension*, *12*(2), 97–108. https://doi.org/10.1080/13892240600861567

Amoussohoui, R., Arouna, A., Bavorova, M., Verner, V., Yergo, W., & Banout, J. (2023). Analysis of the factors influencing the adoption of digital extension services: evidence from the RiceAdvice application in Nigeria. Journal of Agricultural Education and Extension, 1–30. https://doi.org/10.1080/1389224X.2023.2222109

Asioli, D., Mignani, A., & Alfnes, F. (2021). *Quick and easy ? Respondent evaluations of the Becker – DeGroot – Marschak and multiple price list valuation mechanisms*. *July 2020*, 215–234. https://doi.org/10.1002/agr.21668

Atube, F., Malinga, G. M., Nyeko, M., Okello, D. M., Alarakol, S. P., & Okello-Uma, I. (2021). Determinants of smallholder farmers' adaptation strategies to the effects of climate change: Evidence from northern Uganda. *Agriculture and Food Security*, *10*(1), 1–14. https://doi.org/10.1186/s40066-020-00279-1

Badr, M. M. (2019). Farmers' Willingness to Pay for Agricultural Extension Service, A Case Study of Nubaria's Farmers, Egypt. *Asian Journal of Agricultural Extension, Economics & Sociology*, *February*, 1–13. https://doi.org/10.9734/ajaees/2019/v30i230107

Bakker, T., Dugué, P., & de Tourdonnet, S. (2021). Assessing the effects of Farmer Field Schools on farmers' trajectories of change in practices. *Agronomy for Sustainable Development*, *41*(2). https://doi.org/10.1007/s13593-021-00667-2

Bonke, V., Fecke, W., Michels, M., & Musshoff, O. (2018). Willingness to pay for smartphone apps facilitating sustainable crop protection. *Agronomy for Sustainable Development*, *38*(5). https://doi.org/10.1007/s13593-018-0532-4

Cameron, A. C., & Trivedi, P. K. (2022). Machine learning for prediction and inference. *Microeconometrics Using Stata*, 1263–1320. https://cameron.econ.ucdavis.edu/sfu2022/mus2_chapter28.pdf

Carlsson, F., Frykblom, P., & Lagerkvist, J. C. (2005). Using cheap talk as a test of validity in choice experiments. *Economics Letters*, *89*(2), 147–152. https://doi.org/10.1016/j.econlet.2005.03.010

Cash, P., Isaksson, O., Maier, A., & Summers, J. (2022). Sampling in design research: Eight key considerations. *Design Studies*, *78*, 101077. https://doi.org/10.1016/j.destud.2021.101077

Chia, S. Y., Macharia, J., Diiro, G. M., Kassie, M., Ekesi, S., Loon, J. J. A. Van, Id, M. D., & Id, C. M. T. (2020). *Smallholder farmers ' knowledge and willingness to pay for insect-based feeds in Kenya*. 1–25. https://doi.org/10.1371/journal.pone.0230552

Coggins, S., McCampbell, M., Sharma, A., Sharma, R., Haefele, S. M., Karki, E., Hetherington, J., Smith, J., & Brown, B. (2022). How have smallholder farmers used digital extension tools? Developer and user voices from Sub-Saharan Africa, South Asia and Southeast Asia. *Global Food Security*, *32*(August 2021), 100577. https://doi.org/10.1016/j.gfs.2021.100577

Cole, S. A., & Fernando, A. N. (2021). 'Mobile'izing Agricultural Advice Technology Adoption Diffusion and Sustainability. *Economic Journal*, *131*(633), 192–219.

https://doi.org/10.1093/ej/ueaa084

Danso-Abbeam, G., Ehiakpor, D. S., & Aidoo, R. (2018). Agricultural extension and its effects on farm productivity and income: Insight from Northern Ghana. *Agriculture and Food Security*, *7*(1), 1–10. https://doi.org/10.1186/s40066-018-0225-x

Davis, K., Nkonya, E., Kato, E., Mekonnen, D. A., Odendo, M., Miiro, R., & Nkuba, J. (2012). Impact of Farmer Field Schools on Agricultural Productivity and Poverty in East Africa. *World Development*, *40*(2), 402–413. https://doi.org/10.1016/j.worlddev.2011.05.019

Dhehibi, B., Dhraief, M. Z., Frija, A., Ouerghemmi, H., Rischkowsky, B., & Ruediger, U. (2023). A contextual ICT model to explain adoption of mobile applications in developing countries: A case study of Tunisia. *PLoS ONE*, *18*(10 OCTOBER), 1–26. https://doi.org/10.1371/journal.pone.0287219

Elapata, M.S., Suvedi, M., Agwu, A.E., Chanza, C., Sasidhar, P.V.K., Oywaya- Nkurumwa, A., Davis, K., Najjingo Mangheni, M., Dimelu, M.U., Anugwa, I.Q., vonMaltitz, L., Liverpool-Tasie, L.S.O., Tchuwa, F., and Ifeonu, C.F. (2023). Developing the Next Generation of Extension Workers in Sub-Saharan Africa. Partnerships for Innovative Research in Africa (PIRA) Grant Report. East Lansing, Michigan, USA: Alliance for African Partnership, Michigan State University.

Fabregas, R., Kremer, M., Lowes, M., On, R., Zane, G., Alexander, L., Corral, C., Harigaya, T., Misiati, C., Musungu, C., Myers, C., Nawar, A., Nekesa, C., Wanjala Oduor, W., Omenyo, V., Perez, V., & Sheahan, M. (2019). SMS-extension and Farmer Behavior: Lessons from Six RCTs in East Africa. https://www.atai-research.org/wp-content/uploads/2020/05/textfarmers1.pdf.

Fabregas, R., Kremer, M., & Schilbach, F. (2019). Realizing the potential of digital development: The case of agricultural advice. *Science*, *366*(6471). https://doi.org/10.1126/science.aay3038

FAO (2023). Strengthening digital agricultural extension and advisory services in smallholder farming. Rome. https://doi.org/10.4060/cc6267en

FAO & ITU (2022). Status of digital agriculture in 47 sub-Saharan African countries. https://doi.org/10.4060/cb7943en

Filippin, A. (2022). Gender differences in risk attitudes. *IZA World of Labor, October,* 1–10. https://doi.org/10.15185/izawol.100.v2

Gido, E. O., Sibiko, K. W., Ayuya, O. I., & Mwangi, J. K. (2015). Demand for agricultural extension services among small-scale maize farmers: Micro-level evidence from Kenya. *Journal of Agricultural Education and Extension*, *21*(2), 177–192. https://doi.org/10.1080/1389224X.2013.872045

Gosbert, L. S., Athman, K. A., & Jumanne, M. A. (2019). Factors determining crop farmers willingness to pay for agricultural extension services in Tanzania: A case of Mpwapwa and Mvomero Districts. *Journal of Agricultural Extension and Rural Development*, *11*(12), 239–247. https://doi.org/10.5897/jaerd2019.1097

Gray, B., Babcock, L., Tobias, L., McCord, M., Herrera, A., & Cadavid, R. (2018). Digital Farmer Profiles: Reimagining Smallholder Agriculture. *Usaid*, 91.

https://www.usaid.gov/sites/default/files/documents/15396/Data_Driven_Agriculture_Farmer_Profile.pdf

Hanemann, M., Loomis, J., Kanninen, B., Hanemann, M., Loomis, J., & Kanninen, B. (2013). *Statistical Efficiency of Dichotomous Choice Contingent Valuation*. *73*(4), 1255–1263.

Heinzen, R. R., & Bridges, J. F. P. (2008). *methods to estimate the economic value of a pneumococcal vaccine in Bangladesh*. *4*, 481–487. https://doi.org/10.1017/S026646230808063X

Hidrobo, M., Palloni, G., Gilligan, D. O., Aker, J. C., & Ledlie, N. (2022). Paying for Digital Information: Assessing Farmers' Willingness to Pay for a Digital Agriculture and Nutrition Service in Ghana. *Economic Development and Cultural Change*, *70*(4), 1367–1402. https://doi.org/10.1086/713974

Hoang, H. G., & Tran, H. D. (2023). Smallholder farmers' perception and adoption of digital agricultural technologies: An empirical evidence from Vietnam. *Outlook on Agriculture*. https://doi.org/10.1177/00307270231197825

Tambo, J. A., Aliamo, C., Davis, T., Mugambi, I., Romney, D., Onyango, D. O., Kansiime, M., Alokit, C., & Byantwale, T. (2019). The impact of ICT-enabled extension campaign on farmers ' knowledge and management of fall armyworm in Uganda. *PLoS ONE 14(8)*: e0220844. https://doi. org/10.1371/journal.pone.0220844.

Issahaku, H., Abu, B. M., & Nkegbe, P. K. (2017). Does the Use of Mobile Phones by Smallholder Maize Farmers Affect Productivity in Ghana ? Does the Use of Mobile Phones by Smallholder Maize Farmers A ff ect Productivity in Ghana ? *Journal of African Business*, *00*(00), 1–21. https://doi.org/10.1080/15228916.2017.1416215

Javan-Noughabi, J., Kavosi, Z., Faramarzi, A., & Khammarnia, M. (2017). Identification determinant factors on willingness to pay for health services in Iran. *Health Economics Review*, *7*(1). https://doi.org/10.1186/s13561-017-0179-x

Jung, Y., Tian, J., & Bareinboim, E. (2021). *Estimating Identifiable Causal Effects on Markov Equivalence Class through Double Machine Learning*.

Kansiime, M. K., Mugambi, I., Rware, H., Alokit, C., Aliamo, C., Zhang, F., Latzko, J., Yang, P., Karanja, D., & Romney, D. (2022). Challenges and Capacity Gaps in Smallholder Access To Digital Extension and Advisory Services in Kenya and Uganda. *Frontiers of Agricultural Science and Engineering*, *9*(4), 642–654. https://doi.org/10.15302/J-FASE-2021423

Kante, M., Oboko, R., & Chepken, C. (2019). An ICT model for increased adoption of farm input information in developing countries: A case in Sikasso, Mali. *Information Processing in Agriculture*, *6*(1), 26–46. https://doi.org/10.1016/j.inpa.2018.09.002

Khan, N., Siddiqui, B. N., Khan, N., Khan, F., Ullah, N., Ihtisham, M., Ullah, R., Ismail, S., & Muhammad, S. (2020). Analyzing mobile phone usage in agricultural modernization and rural development. *International Journal of Agricultural Extension*, *8*(2), 139–147. https://doi.org/10.33687/ijae.008.02.3255

Kiptot, E., & Franzel, S. (2019). Developing sustainable farmer-to-farmer extension: experiences from the volunteer farmer–trainer approach in Kenya. *International Journal of Agricultural*

Sustainability, *17*(6), 401–412. https://doi.org/10.1080/14735903.2019.1679576

Kosim, M., Aji, J. M. M., & Hapsari, T. D. (2021). The impact of agricultural extension on productivity of smallholder sugarcane farmers in East Java. *IOP Conference Series: Earth and Environmental Science*, *892*(1). https://doi.org/10.1088/1755-1315/892/1/012009

Lee, H. B., Mcnamara, P. E., & Ho, H. (2023). Road accessibility and agricultural extension services in Malawi. *Agriculture & Food Security*, 1–17. https://doi.org/10.1186/s40066-023-00410-y

Lehberger, M., & Grüner, S. (2021). Consumers' willingness to pay for plants protected by beneficial insects – Evidence from two stated-choice experiments with different subject pools. *Food Policy*, *102*(May). https://doi.org/10.1016/j.foodpol.2021.102100

Liu, P., & Tian, X. (2021). Downward Hypothetical Bias in the Willingness to Accept Measure for Private Goods: Evidence from a Field Experiment. *American Journal of Agricultural Economics*, *103*(5), 1679–1699. https://doi.org/10.1111/ajae.12205 Mabaya, E., Dao, A., Traore, E. V., Waithaka, M.,

Mugoya, M., Kanyenji, G., Tihanyi, K. (2021). Burkina Faso 2020 Country Study - The African Seed Access Index. https://ideas.repec.org/p/ags/tasaii/317013.html

Mauki, C., Jeckoniah, J., & Massawe, G. D. (2023). Heliyon Smallholder rice farmers profitability in Agricultural Marketing Co-operative Societies in Tanzania : A case of Mvomero and Mbarali districts. *Heliyon*, *9*(6), e17039. https://doi.org/10.1016/j.heliyon.2023.e17039

McCampbell, M., Adewopo, J., Klerkx, L., & Leeuwis, C. (2021). Are farmers ready to use phone-based digital tools for agronomic advice? Ex-ante user readiness assessment using the case of Rwandan banana farmers. *Journal of Agricultural Education and Extension*, *0*(0), 1–23. https://doi.org/10.1080/1389224X.2021.1984955 Kinkingninhoun

Medagbe, F. M., Floquet, A., Mongbo, R. L., Aoudji, K. N. A., Mujawamariya, G., & Ahoyo Adjovi, N. R. (2023). Gender and access to complex and gender-biased agricultural technology information and knowledge: Evidence from smart-valleys in West Africa. *Outlook on Agriculture, 52(1)*, 22–33. https://doi.org/10.1177/00307270221150659

Miine, L. K., Akorsu, A. D., Boampong, O., & Bukari, S. (2023). Drivers and intensity of adoption of digital agricultural services by smallholder farmers in Ghana. *Heliyon*, *9*(12), e23023. https://doi.org/10.1016/j.heliyon.2023.e23023

Munthali, N., Leeuwis, C., van Paassen, A., Lie, R., Asare, R., van Lammeren, R., & Schut, M. (2018). Innovation intermediation in a digital age: Comparing public and private new-ICT platforms for agricultural extension in Ghana. *NJAS - Wageningen Journal of Life Sciences*, *86–87*(June), 64–76. https://doi.org/10.1016/j.njas.2018.05.001

Ndimbo, K.G, Yu, L.& Ndi Buma, A.A. (2023). ICTs, smallholder agriculture and farmers' livelihood improvement in developing countries: Evidence from Tanzania. Information Developmenthttps://doi.org/10.1177/02666669231165272

Ngailo, J. A., Mwakasendo, J. A., Kisandu, D. B., Mlowe, F. C., & Tippe, D. E. (2016). Rice farming in the southern highlands of Tanzania: management practices, socio-economic roles and production constraints. *European Journal of Research in Social Sciences 4*(4), 28–39.

Ngoma, H., Marenya, P., Tufa, A., Alene, A., Chipindu, L., Matin, M. A., Thierfelder, C., & Chikoye, D. (2023). Smallholder farmers' willingness to pay for two-wheel tractor-based mechanisation services in Zambia and Zimbabwe. *Journal of International Development*, *35*(7), 2107–2128. https://doi.org/10.1002/jid.3767

NSCA (National Sample Census of Agriculture). (2021). The United Republic of Tanzania 2019/20 National Sample Census of Agriculture Key Findings Report for Crops and Livestock Sectors and Fish Farming. August 2021. https://www.fao.org/fileadmin/templates/ess/ess_test_folder/World_Census_Agriculture/WCA_2020/WCA_2020_new_doc/TZA_REP1_ENG_2020.pdf

Ozor, N., Garforth, J. C., Madukwe, M.C. (2011). Farmers' willingness to pay for agricultural extension service: evidence from Nigeria. Journal of International Development. DOI: 10.1002/jid.1849Pfister, H., & Böhm, G. (2008). Emotional functions in decision-making. *Judgment and Decision Making*, *3*(1), 5–17.

Portney, P. R. (1994). The Contingent Valuation Debate: Why Economists Should Care. *Journal of Economic Perspectives 8(4)*- 3–17

PO-RALG (President's Office Regional Administration and Local Government) (2022). Mbeya Regional Secretariat Strategic Plan for the Financial Year 2018/19–2022/23. https://mbeya.go.tz/storage/app/uploads/public/60e/803/a1e/60e803a1ef9bb608372986.pdf

Quandt, A., Salerno, J. D., Neff, J. C., Baird, T. D., Herrick, J. E., Terrence McCabe, J., Xu, E., & Hartter, J. (2020). Mobile phone use is associated with higher smallholder agricultural productivity in Tanzania, East Africa. *PLoS ONE*, *15*(8 August), 1–16. https://doi.org/10.1371/journal.pone.0237337

Ragasa, C., Mzungu, D., Kalagho, K., & Kazembe, C. (2021). Impact of interactive radio programming on agricultural technology adoption and crop diversification in Malawi. *Journal of Development Effectiveness*, *13*(2), 204–223. https://doi.org/10.1080/19439342.2020.1853793

Ranstam, J., & Cook, J. A. (2018). *European Colorectal Congress*. 2–3. https://doi.org/10.1002/bjs.10895

Ristaino, J. B., Anderson, P. K., Bebber, D. P., Brauman, K. A., Cunniffe, N. J., Fedoroff, N. V., Finegold, C., Garrett, K. A., Gilligan, C. A., Jones, C. M., Martin, M. D., MacDonald, G. K., Neenan, P., Records, A., Schmale, D. G., Tateosian, L., & Wei, Q. (2021). The persistent threat of emerging plant disease pandemics to global food security. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(23), 1–9. https://doi.org/10.1073/pnas.2022239118

Rodrigues, K., Dias, F., Abadio, B., Rosenthal, A., Vinicius, M., Finco, A., & Deliza, R. (2016). Willingness to pay more for value-added pomegranate juice (Punica granatum L .): An open-ended contingent valuation. *FRIN*, 6–11. https://doi.org/10.1016/j.foodres.2016.08.039

Samson Olayemi, S., Adeola Ope-Oluwa, A., & Whiteley, A. C. (2021). Evolution of Agricultural Extension Models in Sub-Saharan Africa: a Critical Review. *International Journal of Agricultural Extension and Rural Development Studies*, *8*(1), 29–51. https://ssrn.com/abstract=3794328

Segal, U. Z. I., & Wang, T. A. N. (1993). The Becker-Degroot-Marschak Mechanism Theories and Generalized Utility Theories: Theoretical Predictions and Empirical Observations. *Theory and Decision 34*: 83-97

Shi, L., Gao, Z., & Chen, X. (2014). The cross-price effect on willingness-to-pay estimates in open-ended contingent valuation. *JOURNAL OF FOOD POLICY*, *46*, 13–21. https://doi.org/10.1016/j.foodpol.2014.01.009

Silva, A., Nayga, R. M., Campbell, B. L., & Park, J. L. (2011). Revisiting cheap talk with new evidence from a field experiment. *Journal of Agricultural and Resource Economics*, *36*(2), 280–291.

Silvestri, S., Richard, M., Edward, B., & Dharmesh, G. (2020). Going digital in agriculture : how radio and SMS can scale-up smallholder participation in legume- based sustainable agricultural intensification practices and technologies in Tanzania. *International Journal of Agricultural Sustainability*, *0*(0), 1–12. https://doi.org/10.1080/14735903.2020.1750796

Subrahmanian, R., Gattorno, G., Grainger, P., Guidi, A., Kanwar, S., Kedia, M., & Sorgner, A. (2022). Bridging the Digital Literacy Gender Gap in Developing Countries.Policy Brief. https://www.t20indonesia.org/wp-content/uploads/2022/09/TF2_BRIDGING-THE-DIGITAL-LITERACY-GENDER-GAP-IN-DEVELOPING-COUNTRIES.pdf

Sumo, T. V., Ritho, C., & Irungu, P. (2023). Determinants of Smallholder Rice Farmers' Willingness-to-Pay for Private Extension Services in Liberia: The Case of Gibi District. *Sustainability*, *15*(19). https://doi.org/10.3390/su151914300

Sylla, A. Y., Mahama Al-Hassan, R., Egyir, I. S., & Anim-Somuah, H. (2019). Perceptions about quality of public and private agricultural extension in Africa: Evidence from farmers in Burkina Faso. *Cogent Food and Agriculture*, *5*(1). https://doi.org/10.1080/23311932.2019.1685861

Tibshirani, R. (1996). Regression shrinkage and selection via the Lasso. Journal of the Royal Statistical Society. Series B. 58(1), 267–288.

Ulimwengu, J., & Sanyal., P. (2011). Joint Estimation of Farmers" Stated Willingness to Pay for Agricultural Services. *IFPRI Discussion Paper 01070. Washington, DC: IFPRI*. *January 2011*, 2011.

Wang, S., Ji, B., Zhao, J., Liu, W., & Xu, T. (2018). Predicting ship fuel consumption based on LASSO regression. *Transportation Research Part D: Transport and Environment*, *65*(xxxx), 817–824. https://doi.org/10.1016/j.trd.2017.09.014

Wertenbroch, K. and Skiera, B. (2002). Measuring Consumers ' Willingness to Pay the Point of Purchase. *Journal of Marketing Research*, *39*(2), 228–241.

Wilson, C., & Tisdell, C. (2002). OLS and Tobit Estimates: When is Substitution Defensible Operationally? *Economic Theory, Applications and Issues*, *January 2002*, 1–9.

Witteveen, L., Lie, R., Goris, M., & Ingram, V. (2017). Design and development of a digital farmer field school. Experiences with a digital learning environment for cocoa production and certification in Sierra Leone. *Telematics and Informatics*, *34*(8), 1673–1684. https://doi.org/10.1016/j.tele.2017.07.013

Wongprawmas, R., Pappalardo, G., & Canavari, M. (2016). Willingness-to-Pay for Multiple Units of Eco- Friendly Wheat-Derived Products : Results From Open-Ended Choice Experiments Willingness-to-Pay for Multiple Units of Eco-Friendly Wheat-Derived Products : Results From Open-Ended Choice Experiments. *Journal of Food Products Marketing*, *22*(6), 658–682. https://doi.org/10.1080/10454446.2015.1121438

Xiong, H., Payne, D., & Kinsella, S. (2016). Peer effects in the diffusion of innovations: Theory and simulation. *Journal of Behavioral and Experimental Economics* , *63*, 1–13. https://doi.org/10.1016/j.socec.2016.04.017

Yang, C., Delcher, C., Shenkman, E., & Ranka, S. (2018). Machine learning approaches for predicting high cost high need patient expenditures in health care. *BioMedical Engineering OnLine*, *17*(S1), 1–20. https://doi.org/10.1186/s12938-018-0568-3

Zondo, B. S., & Baiyegunhi, L. J. S. (2021). Determinants of Willingness to Pay (WTP) for organic fertiliser : a case of smallholder potato farmers in KwaZulu-Natal , South Africa. *Journal of Agriculture and Rural Development in the Tropics and Subtropics*, *122*(2), 257–268.