An Evaluation of farmers' digital literacy and awareness on the adoption and implementation of bundled digital innovations in Uganda

INITIATIVE ON
Rethinking
Food Markets

Farmer picking up input from EzyAgric on boarded agro-input dealer

December 2024

Sylvester Ogutu, Enoch Kikulwe, Susan Ajambo, Stewart Ategeka and Eliud Birachi

Alliance of Bioversity International and CIAT & EzyAgric

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Global agri-food systems face numerous challenges, including the adverse effects of climate change, low productivity, limited adoption of technologies, and restricted access to input and output markets. These constraints contribute to increased food insecurity, decreased income from agriculture, and stagnated growth rates in many agrarian economies. Digitizing the agriculture sector presents a sustainable solution to these challenges by providing critical information that supports optimal decision-making, enhancing efficiency and productivity. However, the widespread adoption of digital innovations in this sector is hindered by low awareness of existing technologies, limited digital literacy, and prevailing social norms and power dynamics affecting various population segments, particularly women and youth.

To overcome these barriers, campaigns aimed at improving digital literacy and raising awareness is essential for promoting the uptake and use of digital innovations. Despite the importance of these initiatives, studies that quantify the impact of such interventions on the adoption and use of bundled digital innovations remain limited. This evaluation report, first, examines the effects of awareness creation and digital literacy trainings on the adoption of bundled digital innovations, differentiated by gender. Second, it evaluates the impact of digital literacy training on input use (improved seeds, fertilizer, agrochemicals (fungicides and herbicides) and mechanization), crop yields (for at least two major annual crops in the study area: maize and beans and two cash crops (banana and coffee), and income, all categorized by gender and other socio-economic characteristics.

Data for this study were obtained from a randomized controlled trial (RCT), collected over two waves: a baseline conducted in September 2023 and a follow-up in September 2024. The treatment group comprised 253 households from three districts in Uganda, who received digital literacy training along with basic agronomic training as part of the intervention. In contrast, the control group consisted of 284 households from two districts. Ordinary least squares (OLS) regression models were employed since the covariates were balanced between the treatment and control groups at both the baseline and follow-up stages. ANCOVA was also utilized for validation purposes, incorporating pre-treatment variables to enhance model estimates. The results indicate an attrition rate of 4.5%, with no significant differences observed across the various explanatory variables. This suggests that attrition is non-systematic. The balance test scores show no evidence of differences in covariates between the treatment and control groups, which supports the use of OLS regression for empirical estimation. The intervention led to a significant increase in the uptake of improved seeds, as well as a positive trend of gross revenues from agricultural production and increased consumption expenditures on both food and non-food items. This study suggests that creating awareness and providing digital literacy training can enhance the adoption of productivity-enhancing inputs, such as improved seeds. Additionally, it is essential to adopt an inclusive, gender-sensitive approach to ensure that awareness and training campaigns have a wider impact.

1. Introduction

Globally, the agricultural industry is one of the leading employers and a primary source of livelihood, significantly contributing to the economic growth of many low- and middle-income countries (Mirembe, 2021). However, the sector faces several challenges, including the impacts of climate change, limited market access, and low productivity. These issues have led to production values falling well below established average yield potentials, despite an increasing demand for food and agricultural products. This situation has resulted in food insecurity and nutrition-related illnesses while hindering overall economic development (Alwang et al., 2019; FAO et al., 2020; Ligon & Sadoulet, 2018).

The persistence of these challenges within the agri-food system can partly be attributed to information constraints and low levels of technology adoption worldwide (Fafchamps et al., 2020). However, advancements in agricultural digitization present hope, as they incorporate various innovations capable of addressing these issues. These innovations have the potential to improve agricultural production efficiency, productivity, quality, and profitability while enhancing market access. Ultimately, this progress can increase rural incomes, provide food and raw materials, and support the growing global population that heavily depends on the agricultural sector (Erickson & Fausti, 2021; FAO et al., 2020).

Digital agriculture refers to a set of technological innovations that digitally collect store, analyse and share information electronically along the agricultural value chain (Runck et al., 2022). Digital innovations in the agricultural arena can be inform of physical devices including machines and sensors or software tools like advisory apps, farm management software and online platforms that are run on computers, smartphones, tablets and other electronic devices (Finger, 2023; Tummers et al., 2019). Harnessing the power of these digital technologies, agricultural chain actors can readily interact with agricultural extension and advisory service providers (Anderson, 2020), and access information that helps them make informed decisions regarding fertilizer and agro-chemical use, input and output market access and other farm management operations (Mirembe, 2021; Tummers et al., 2019). Artificial intelligence (AI), remote sensing, robotics, blockchain, and quantum computing are among some of the digital innovations that are gradually filling the communication and data exchange gap in the agriculture sector (Balyan et al., 2024).

The agriculture industry in the global north is already ripping the benefits of digitization by employing digital tools to provide farmers with real-time weather updates, market pricing, electronic business transactions (e-commerce), and extension services (Das, 2023). Farm operations like milking, weed detection and control, soil moisture monitoring, temperature, and soil nutrient level observation are other agricultural operations that are being effectively managed using digital innovations (Ane & Yasmin, 2019; Balyan et al., 2024; Singh et al., 2023). Agricultural systems in Sub-Saharan Africa could benefit greatly from replicating application of digital innovations to negate constraints like credit, input and output market access, weather information and seasonality, extension, labour allocation among others that is confronting small-scale farmers (Choruma et al., 2024). Consequently, there would be improvements in information flow, input and produce marketing, and reduced transaction costs along the agri-food value chains (Deichmann et al., 2016; Trienekens, 2011). Thus, fostering increased income levels, economic inclusion for youth and women in agriculture and overall boost in climate resilience (Tsan et al., 2019; World Bank, 2023). Despite the wide variety of benefits affiliated with digital innovations in the agriculture sector, its adoption and use remains low in most African countries. Promptly addressing the bottlenecks hindering the wider adoption of digital innovations is paramount to enabling smallholder farmers to realize the full benefits of agricultural digitization.

Several empirical studies have analysed factors limiting adoption of digital innovations in agriculture. Ma & Wang, (2020) for instance, evaluated the impact of digital technologies on adoption of sustainable agricultural practices. Their results showed that household size, membership in agricultural cooperative, education level, age, farm size and gender significantly influenced uptake of digital technologies. Poushter, (2016) equally revealed that digital technology uptake was influenced by divide between genders. Other studies have pointed out the high technology costs, high level of automation of the technologies, value of farm produce (Revenue from produce), limited internet and lack of the necessary digital infrastructure as the limiting factor (Abdulai et al., 2023; Baumüller, 2018; Birner et al., 2021; Finger et al., 2019; Rotz et al., 2019; Shang et al., 2021; Williamson & Hartley, 2024). What is most pertinent and cross cutting across all the studies however is the challenge of low digital literacy, limited information access and gender disparities (Hassani et al., 2023; Magesa et al., 2023; Pierpaoli et al., 2013; Tsan et al., 2019), which solely reflect the ability of the individuals to adopt and use digital innovations and must be the focal point of action if mass scaling of agricultural digital innovations is to be achieved. Digital awareness campaigns and literacy trainings are some of the core tools available for tackling this challenge, however, the impact of such interventions on adoption and uses of digital innovations as well as other broad farm household outcomes like farm revenues, consumption expenditure, asset values, and food security are rarely covered in empirical literature. Understanding such impacts would help to inform policy decisions on adoption and use of digital innovations in agriculture and providing evidence that can be used to motivate potential stakeholders to promote uptake of digital innovations in the agricultural sector.

2. Background and Project description

The agricultural digitization landscape in Uganda is one that keeps evolving with emerging global trends with a multiplicity of digital innovations being developed and rolled out for use in the agri-food value chain each year. Digital extension is one area were the country has greatly excelled with some scholars recognising it as the birthplace of digital extension in Africa (Ledermann et al., 2024). Information and communication technology (ICT) tools like SMS, videos, web-based applications, button and smart phones are used to deliver these extension services (Amadu & McNamara, 2019; Campenhout, 2021). The urgent need for adoption and use of digital innovations in Uganda's agriculture was accelerated following the covid19 pandemic which disrupted extension service delivery and access to input and output markets (Mirro et al., 2020; Rwamigisa, 2020; World Bank, 2023).

Presently, one of the most successful and powerful digital innovations in Uganda is the EzyAgric platform that has been developed by Akorion Limited. The App offers bundled agricultural services including connecting small and large-scale farmers to agricultural service providers, agro-input dealers, soil laboratories, meteorology departments, produce markets and agricultural financing. It further acts as a knowledge hub for crop related extension services including pest and disease diagnoses and management and provides a unified platform for profiled and registered agri-food value chain actors to meet and trade while supporting inclusive production and delivering financial and marketing services to the farmer's doorway. The EzyAgric platform has over 300,000 registered farmers, but only 20% actively use it. The app offers five key bundled services including 1. Farm Manager which offers farming guidance and farm record management advice; 2. Agri-shop for purchasing certified inputs like seeds and tools at affordable prices; 3. EzyCredits for loans redeemable in the Agri-shop based on user activity; 4. Agri-Extension for tailored agronomic advice, and 5. Produce Market for linking farmers to buyers with mobile payments. The platform generally relies on community-based agents with smartphones to deliver last-mile services, even though a toll-free and SMS option exists for susceptible farmers who do not have access to smart phones.

Despite a hefty $25 million investment in the development of the platform and the range of benefits embedded in the EzyAgric platform, its adoption and active usage remains limited. (Mirembe et al., 2023), reveal that low digital literacy levels and lack of digital infrastructure are behind low uptake and use of digital innovations in Uganda. Indeed, a scoping visit conducted in 2023 in Uganda under the CGIAR Initiative on Rethinking Food Markets showed that low digital literacy, limited awareness and low level of responsiveness to digital innovations biased by gender differences were responsible for the low uptake and use of the EzyAgric services. Consequently, awareness creation around the EzyAgric platform, digital literacy and some basic agronomic training were prioritized as interventions for addressing this constraint with the intent to motivate farmers to embrace the platform and harness the full range of benefits that come with the innovation. To evaluate the performance of the proposed interventions before making the decision to scale out, a randomised controlled trial (RCT) study was designed and implemented in five districts of Uganda (Mubende, Luwero, Mityana, Kasanda, and Nakaseke). Key outcomes of interest during this evaluation included intermediate outcomes like adoption and use of the technology and the long-term impacts included behavioural changes in income, food security, consumption expenditure and assets.

3. Overview of project implementation process

3.1. Selection of the digital platform

The project started by identifying digital platforms offering innovative cross-value chain services in Uganda's agricultural sector. An online search and meetings with identified actors using the snowballing method revealed 32 digital platforms. As part of a scoping study, key informant interviews were conducted with each platform to understand how digital innovations addressed inefficiencies and enhanced inclusiveness in agricultural value chains. To aid the selection of the most promising innovation, a nine-point criterion was developed and validated through a multi-stakeholder meeting. The criterion included; 1) the number of services bundled; 2) the number of value chains operated in; 3) the salient features of the innovations; 4) the gender and youth responsiveness of the innovations; 5) the geographical coverage of the innovation (including the number of active users); 6) sustainability; 7) the size of the business; 8) clear plans of the innovators; and 9) the level of scaling readiness (1-conceiving of ideas, 2-design of the idea, 3-proofing/piloting, 4-beyond the piloting and 5- nationally available to serve). The assessment showed that neither the design nor the deployment of most innovations paid attention to the integration of gender thus the overall scores on the gender-responsive criteria were low. Also, most innovations were ranked at stage 4 on the scaling readiness criteria indicating a gap in their uptake. Based on the assessment, Agri-logistics and EzyAgric by Akorion Limited obtained the highest scores in the scaling readiness assessment. EzyAgric was finally picked because of high potential for impact and limited finances available for implementation. Like the other innovations, the active usage of the EzyAgric platform by the farmers was low and acknowledged as one of the most important challenges to scaling, underscoring the need to increase the awareness of the farmers about the platform. The project collaborated with EzyAgric to develop and test strategies for raising farmers' awareness of the digital platform, specifically its agri-shop component, which streamlines agro-input supply chains and tackles the issue of counterfeit products.

3.2. Implementation of the RCT

The implementation of the RCT started with the on-boarding of agro-input dealers in October 2023, in five districts of central Uganda. The districts included Nakaseke, Luwero, Mityana as treatment districts and Mubende, and Kasanda were control districts (See figure 1). A two-stage sampling procedure was employed: first, we purposively selected the districts from a long list of EzyAgric of potential expansion sites. Within the selected districts, EzyAgric on boarded 80 agro-input dealers. Second, comprehensive listings of farmers were generated within the radius served by each on boarded agro-input dealer with aid of the local council authorities. A minimum of 7 farmers were randomly selected from each listing, totalling to 560 farmers of which 260 were in the treatment sites and 300 were in the control sites. A baseline study was conducted between November and December 2023.

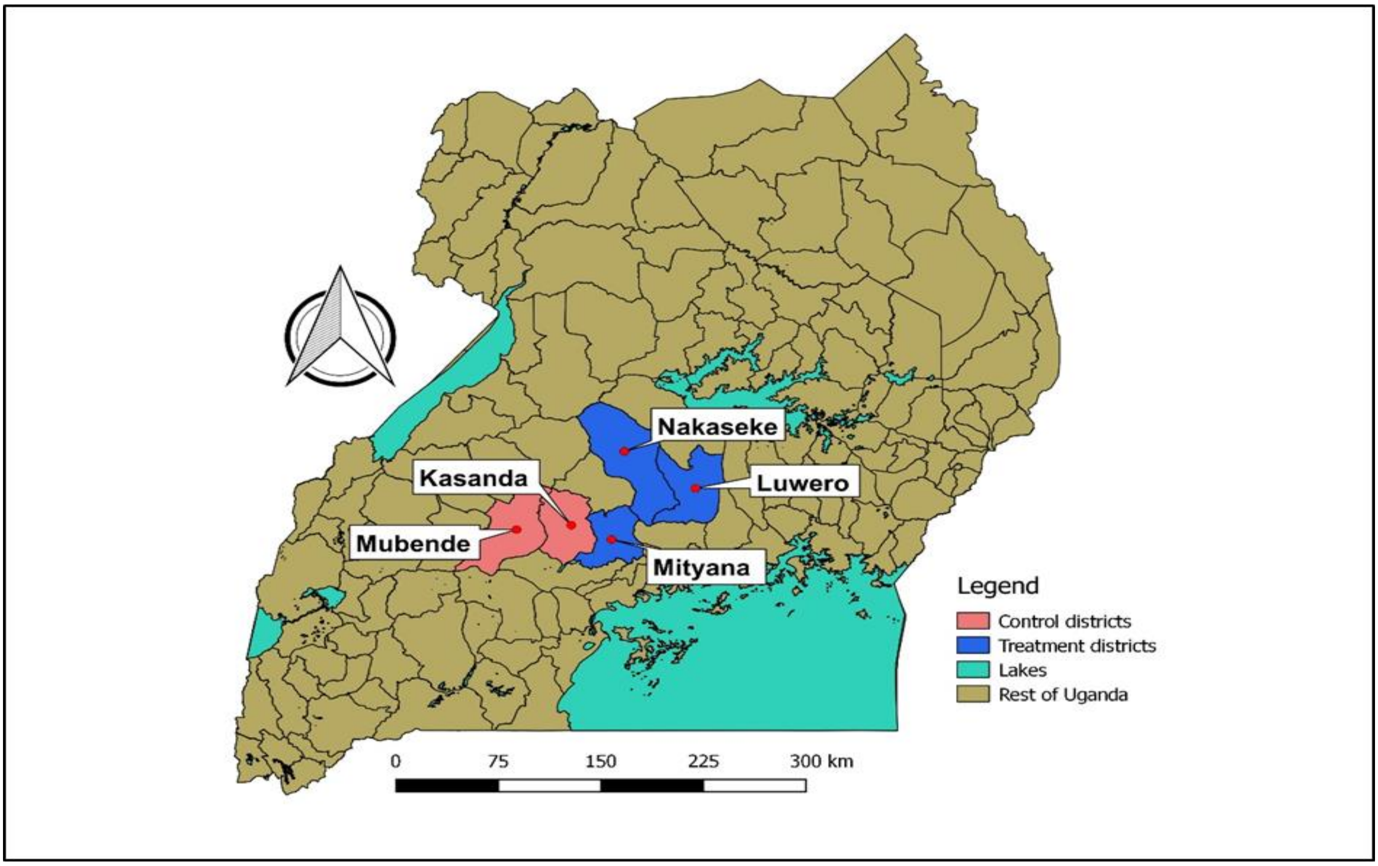


Figure 1: Map of Uganda showing the study districts

The treatment group of farmers were subjected to two training sessions, while no training was undertaken in the control districts. The first training session took place in January and February 2024, while the second session was undertaken in May and June 2024. The training consisted of two components: (1) digital literacy to understand the EzyAgric App interface and how to use it for ordering inputs and accessing agro-advisory (e-extension) using USSD codes and smartphone application, and (2) safe use and handling of agrochemicals (identification of the level of toxicity, proper storage, proper application, and ensuring the purchase of genuine products). Trainings were conducted first at the sub county level focusing on introducing the farmers to the App and downloading it. Second trainings were at the village level in small groups focusing on profiling farmers, testing the USSD service (e-extension), and onsite ordering of inputs (seed and agrochemicals).

The farmers surveyed at baseline were followed-up in September 2024, to gather information on key variables that were elicited at baseline following implementation of interventions in the three treatments districts. During the follow-up study, the survey team was only able to track and obtain information from 512 farmers with 24 dropping out, representing a 4.5% attrition rate. With the follow-up survey complete, the impact evaluation process was now activated with the focus mainly on intermediate outcomes (digital innovation awareness and use (adoption), since the follow-up study came immediately the interventions had been completed before tangible long-term impacts can be attributed to the effects of the intervention. The key objectives of the evaluation were to 1. Examine the effects of awareness creation and digital literacy trainings on the adoption of bundled digital innovations, differentiated by gender and 2. To evaluate the impact of digital literacy training on input use (improved seeds, fertilizer, fungicides, agro-chemicals, yield and income) categorized by gender and other socio-economic characteristics. The framework guiding the overall evaluation process is illustrated in figure 2 below.

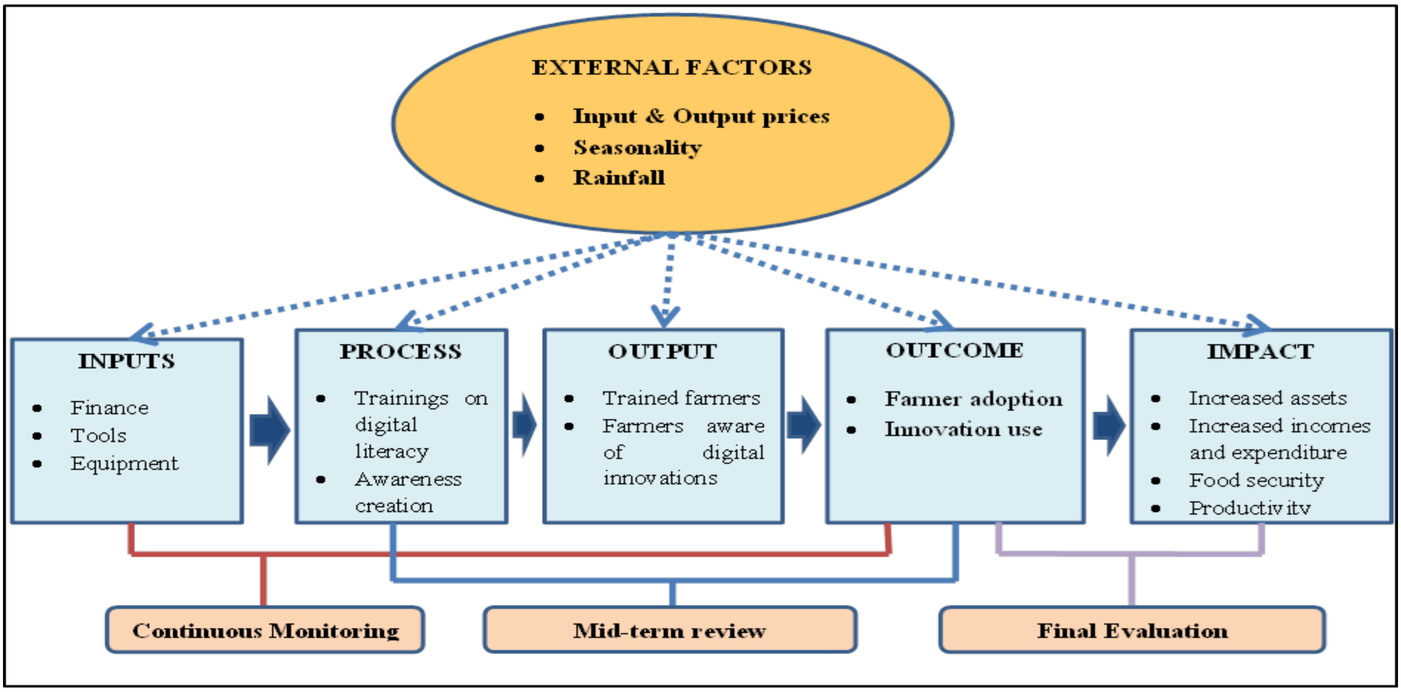


Figure 2: Impact evaluation pathway for the EzyAgric platform

The input section in figure 2; represents the financial, material, human and other resources that were utilized throughout the evaluation process. Process include the farmer mobilization exercise, merchant on-boarding, awareness creation campaigns, digital literacy training, basic agronomy training and other interventions that were introduced in the treatment districts. Outputs are the quantifiable products like number of farmers that were trained on digital literacy and those that accessed the awareness campaigns. Outcome are the immediate behavioural changes realized following the implementation of interventions (Number of farmers adopting and using the digital innovations and services) and finally the impact are the long term changes expected of the project following the interventions (increased assets, income, consumption expenditure, productivity and improved food security and nutrition).

4. Experimental design and intervention

In this section, the set-up of the experiment, allocation of farming households into treatment and control groups and the interventions given to the treatment group is discussed. Only one treatment arm (group) was identified for this study with three districts including Luwero, Nakaseke and Mityana being allocated to it. The treatment arm comprised 252 randomly selected farming households at baseline. The interventions introduced to the farming households in the treatment arm included the digital awareness, digital literacy training and basic agronomy practice training. The second group formed the control arm which was not subject to any intervention. About 284 farming households from two districts (Mubende and Kasanda) were randomly recruited into this group at baseline. Detailed structure of the design and allocation of the farming households into these groups is illustrated in figure 3 below. Data collection from both the treatment and control sites were done at two levels: the first level was the population level based on the EzyAgric database capturing the results emerging from the interventions such as number of orders, quantity and value of inputs, number of farmers accessing e-extension among others. This captured the data before and within the intervention periods. At the second level, data was collected from a sample of farmers (base-line and follow-up survey) in both intervention and control sites.

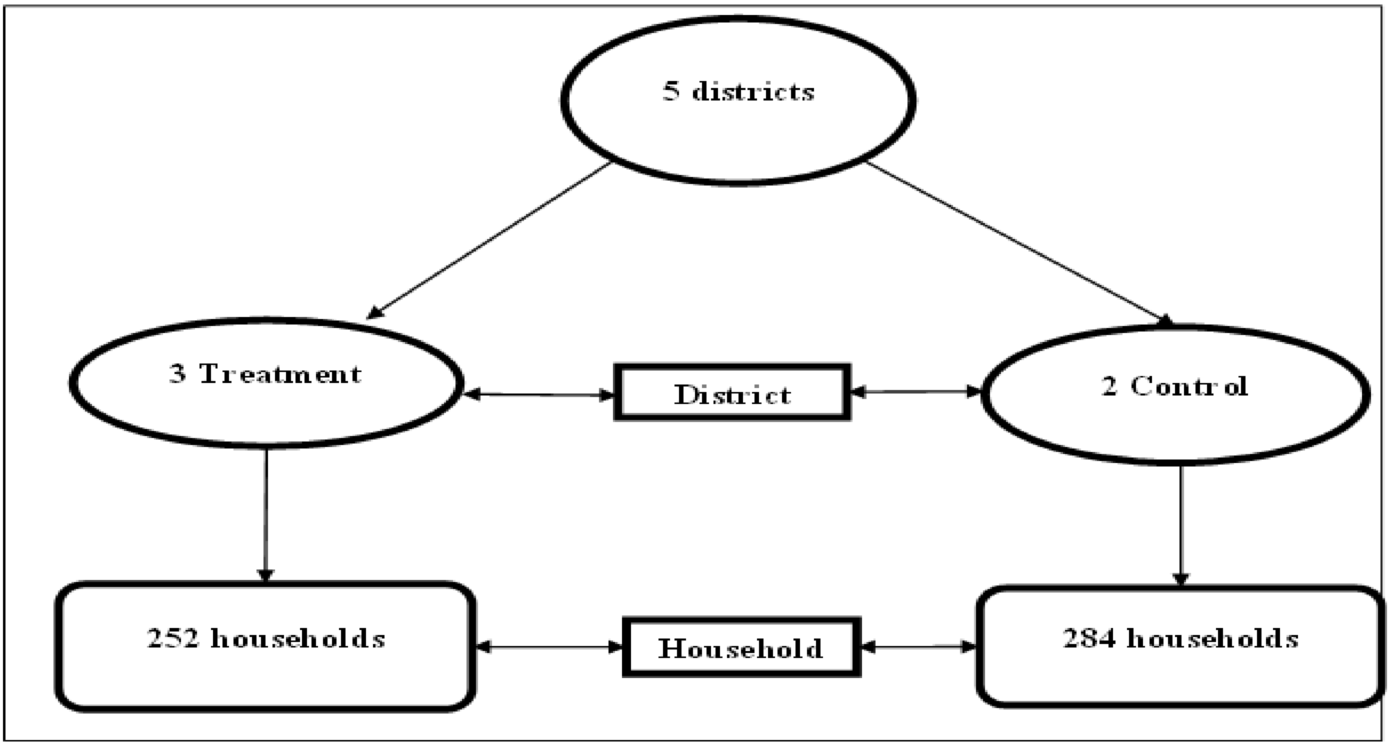


Figure 3: *Allocation of participants into treatment and control groups*

5. Empirical estimation procedure

In this section, the analytical methods followed for evaluating the impact of the implemented interventions are documented**.** Non-compliance in randomized experiments is quite ubiquitous, where subjects exposed to treatment who are expected to take-up rather do not and those in the control not expected to receive the treatment (DiTraglia et al., 2023; Gerber & Green, 2012). This, however, seldom occur, with subjects in the control taking up the treatment and those in the treatment not taking up the treatment. To address noncompliance, we estimate Intension-to-treat (ITT) that estimate the causal effects based on randomization, regardless of whether subjects actually received the treatment (Gerber & Green, 2012). The ITT is specified as:

$$Y_i = \alpha + \beta_1 T_j + \vartheta X_j + \varepsilon_i \qquad (1)$$

where Y_i represents observed outcome variables – such as application of inputs, productivity, consumption expenditure (food and non-food) and value of assets; T_j is the treatment variable representing the awareness creation on the use of smartphones and village agents to access EzyAgric's bundled services; X_j are pre-treatment covariates that are included to improve the precision of our estimates; α, β_j and ϑ parameters of the variables explained above and ε_i captures individual-specific errors.

Mckenzie, (2012) reports of improvement in statistical power of estimated impacts when the lag of the baseline outcome variables are included in an Analysis of Covariance (ANCOVA) estimator, specified in equation 2. Through this, we are able to account for some of the variability in the outcome variables to improve precision and improve statistical power.

$$Y_{iPOST} = \alpha + \beta_1 T_j + \gamma Y_{iPRE} + \vartheta X_j + \varepsilon_i \qquad (2)$$

where Y_{iPOST} and Y_{iPRE} are respectively the outcome variables for the endline and baseline; all other variables are as earlier on defined above. α, β_j, γ and ϑ are the ANCOVA parameter estimates.

6. Results and Discussions

In this section of the report, we present findings from the empirical analyses. These results are grouped into three (3) main headings: First, we present descriptive statistical results on the awareness, sources of information and use of the EzyAgric digital tools (such as transactions related to inputs (seeds, fertilizer and agro-chemical orders, agronomic practices adopted), Knowledge of the EzyAgric platform and innovations, disaggregated by gender. Next are the results on the impacts of the intervention on awareness of EzyAgric digital platform, agricultural input use and productivity. Results on the welfare impacts such as household consumption expenditure and value of assets are then presented. Prior to presenting these results, we briefly present results on balance test and attrition bias.

6.1. Balance test

A fundamental condition needed for the use of randomized controlled trials for identification of the causal impacts of intervention is the absence of differences between subjects prior to their assignment to either of the treatment arms (i.e. treated or control) (Glennerster & Takavarasha, 2013). Satisfying this criterion is quite crucial in that any observed impacts at the end of the intervention can inform our confidence in informing conclusions. Several balanced tests were undertaken using the baseline data, the estimates of which are displayed on table 1. Other balance test scores are in the appendix (Table 1A.1, 1A.2, and 1A.3)

Table 1: Balance test estimates

Variable	Pooled Sample	Control	Treated	Abs. Mean diff.	Observations (N)
Gender (1=*Female* 0=*Male*)	0.191 (0.393)	0.158 (0.022)	0.221 (0 .024)	0.063** (1.163)	536
Age (years)	51.414 (13.701)	50.087 (0.831)	52.623 (0.812)	2.535** (1.163)	536
Education level (years)	7.669 (4.038)	7.468 (0.161)	7.854 (0.151)	0.3867 (0.343)	536
Household size (count)	6.590 (2.603)	6.603 (0.161)	6.577 (0.151)	0.0259 (0.221)	536
Married head (yes/No)	0.794 (0.017)	0.848 (0.022)	0.744 (0.026)	0.104*** (0.035)	525
Head is group member (Yes/No)	0.679 (0.020)	0.692 (0.029)	0.667 (0.028)	0.026 (0.040)	536
Farm size (acres)[1]	7.614 (0.490)	10.482 (0.908)	5.031 (0.387)	5.451 (0.953)	536
Distance to extension agent (km)	3.554 (0.355)	3.993 (0.281)	3.159 (0.626)	0.833 (0.712)	536
Distance to agro-dealer (km)	2.673 (0.209)	2.149 (0.195)	3.255 (0.383)	1.106	536
Distance to village market (km)	1.741 (0.105)	1.936 (0.155)	1.566 (0.141)	0.370 (0.209)	536
Observations	536	254	282		

Note: *This table presents results of a balanced test on a set of socio-demographic covariates. Values in parentheses are standard errors. *, ** and *** respectively denote significance at 10, 5 and 1% respectively.*

6.2. Attrition bias

Given that not all subjects in our experimental setup at the baseline were reached in the endline despite the tremendous efforts, we fit a probit model to test for systematic attrition bias between the treatment and control subjects and the relationship of the attrition to pretreatment variable values following (Fitzgerald et al., 1998). The results from the follow-up survey recorded 4.5% attrition rate (5% in the control and 4% in the treatment group), with the results in Table 2 showing that none of the covariates fitted in the probit model for analysis of the attrition bias is statistically significant; suggesting the absence of systematic difference among farming households who dropped out from the follow-up survey.

Table 2: Probit estimates of test of attrition bias

Variables	Coefficients
Female	0.010 (0.037)
Age(years)	0.000 (0.001)
Education(years)	0.001 (0.001)
Household size	0.001 (0.003)
Married(Yes/No)	0.023 (0.037)
Group member(Yes/No)	0.006 (0.020)
Farm size(in acres)	0.000 (0.000)
Distance to extension agent(km)	-0.001 (0.001)
Distance to Agro-input dealer(km)	0.000 (0.002)
Distance to village market(km)	-0.002 (0.004)
Observations	536

Note: *Figures in parenthesis are standard errors. The outcome variable, attrition is denoted by a value of 1 if the farming household is absent during follow-up and 0 otherwise.*

6.3. Awareness, information sources and use of EzyAgric platform and innovations

One of the key intermediate outcomes expected of the intervention was increased awareness and use of EzyAgric innovations. Results of awareness levels, use of EzyAgric innovations and the various sources of information about the EzyAgric platform are displayed in figures 4, 5 and 6, respectively. In Figure 4, the proportion of those aware of the EzyAgric platform is shown to have increased fivefold following the intervention compared to the control.

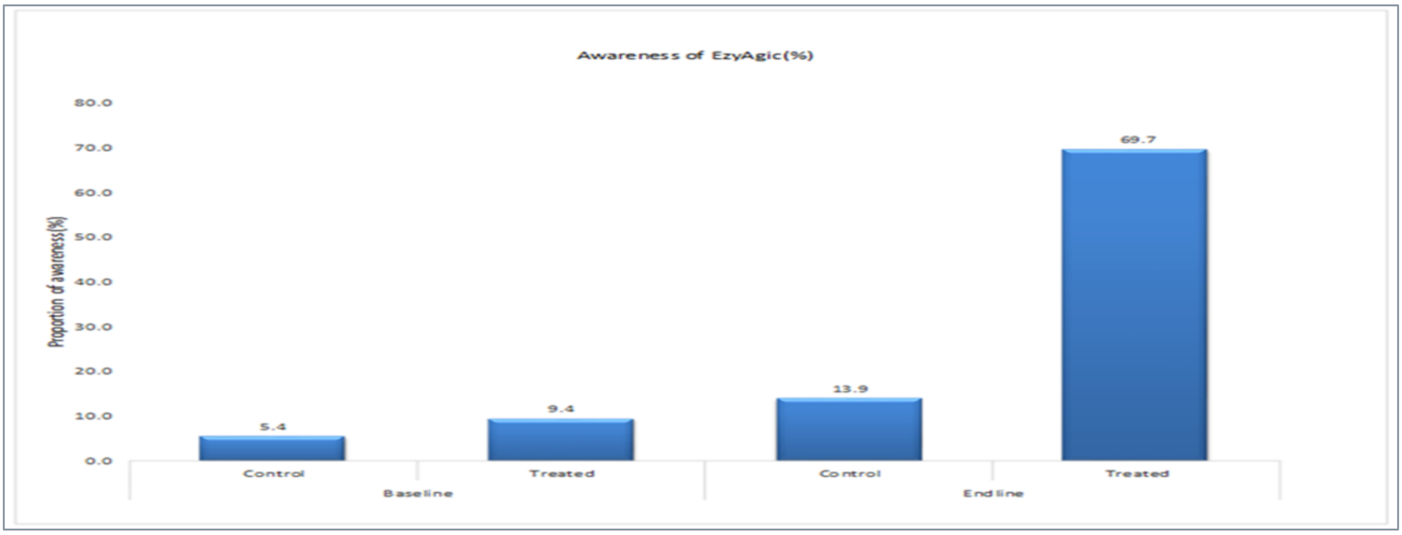


Figure 4: Awareness of EzyAgric platform.

The information source about the EzyAgric platform within the intervention districts was predominantly through the EzyAgric Staff and agents. Farmers in the control districts however accessed some information about the platform and its innovations, mainly through interaction with fellow farmers (See figure 5). The findings reflect the importance of using EzyAgric staff and agents in the scaling of the innovations to the agricultural communities. The effect of farmer social networks should however not be downplayed as a tool for scaling of digital innovations as shown by its potential for information dissemination in the control sites.

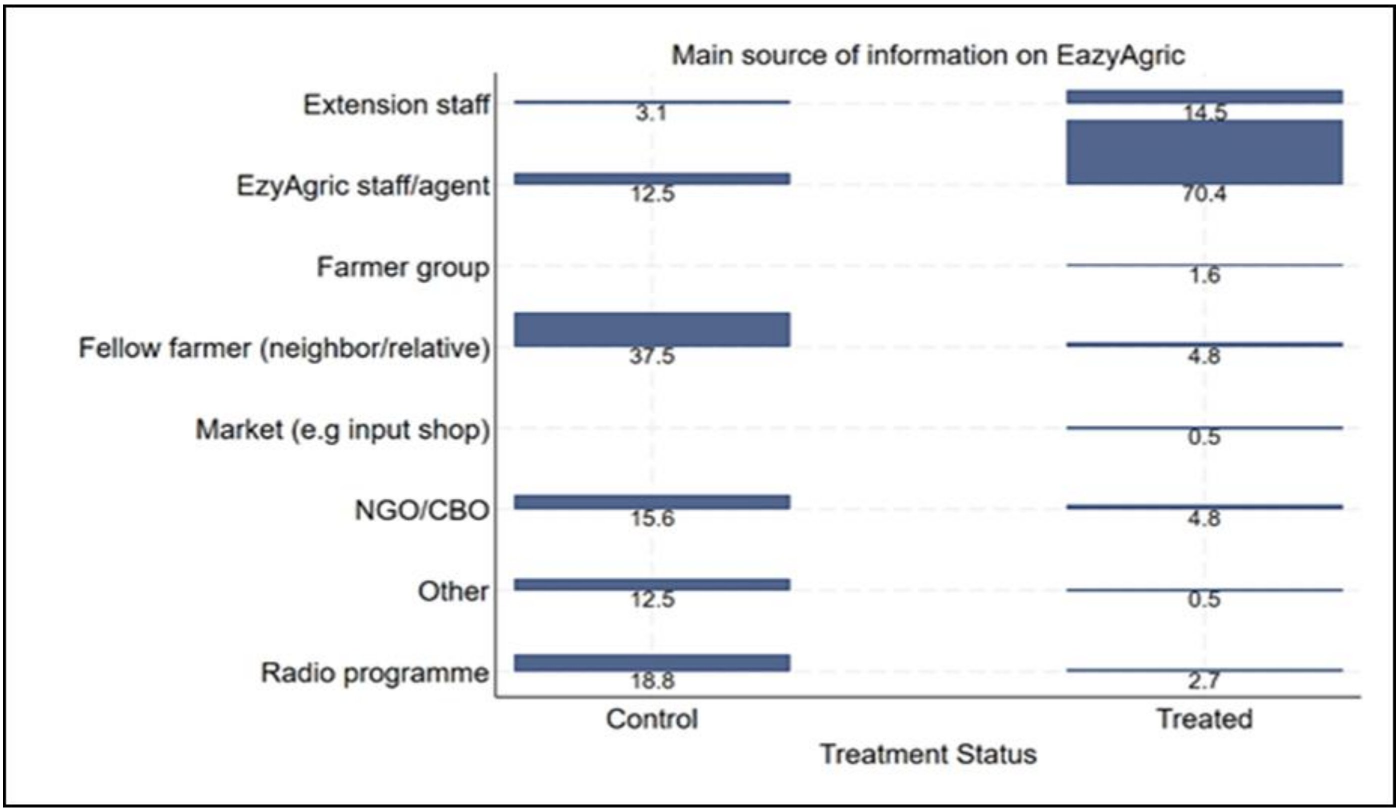


Figure 5: ***Information sources about the EzyAgric platform and its bundled innovations***

Statistics on the use of EzyAgric platform by farmers in treatment and control sites is displayed in figure 6. The overall outlook of the figure reveals that the proportion of farming households using the EzyAgric application for genuine and improved seed sourcing and advisory services marginally increased in the treatment sites, as opposed to a declining use trend recorded in the control districts following the interventions (see figure 6). We note however that while there is a step rise in awareness about the EzyAgric platform (see figure 4), its use application is not commensurate to the percentage increase in awareness levels about the EzyAgric platform. This possibly could be attributed to the fact that the follow-up study was conducted right after the completion of the interventions with limited time for the farmers to take up and use most of the interventions as the cropping season was yet to set in.

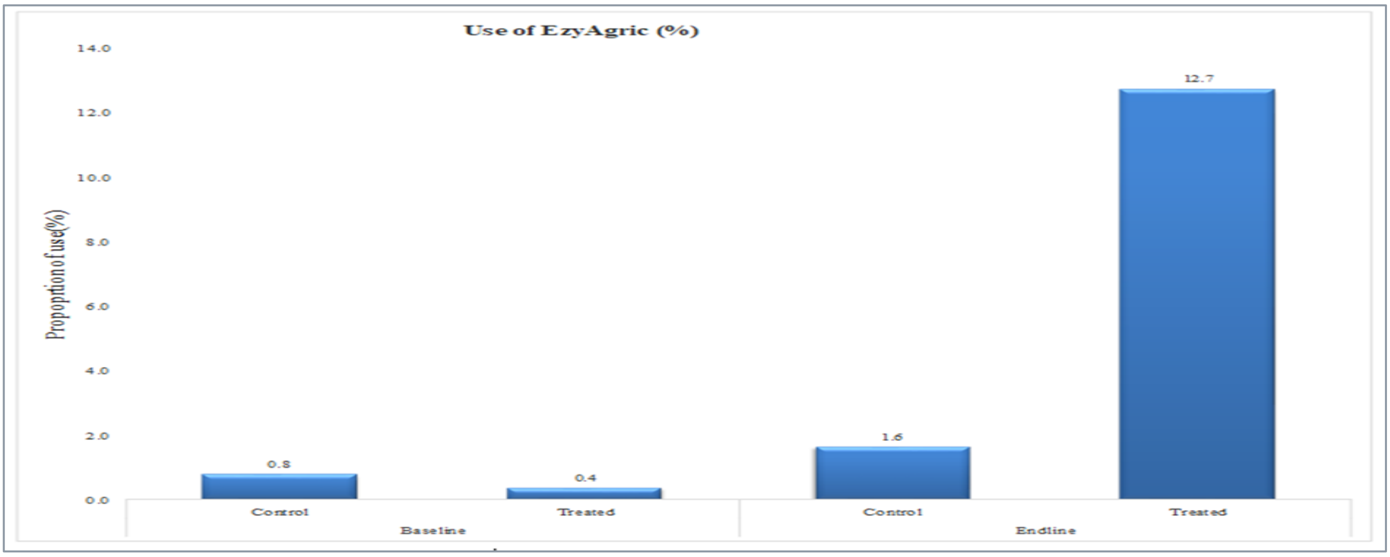
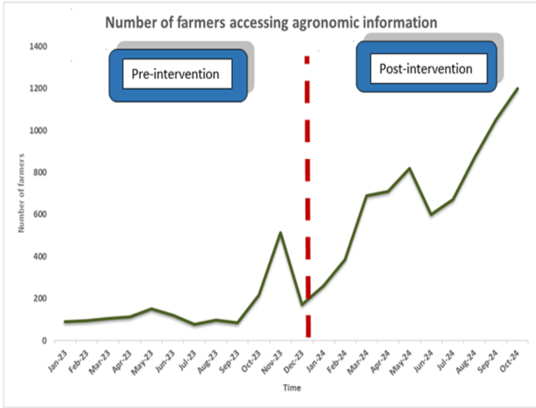


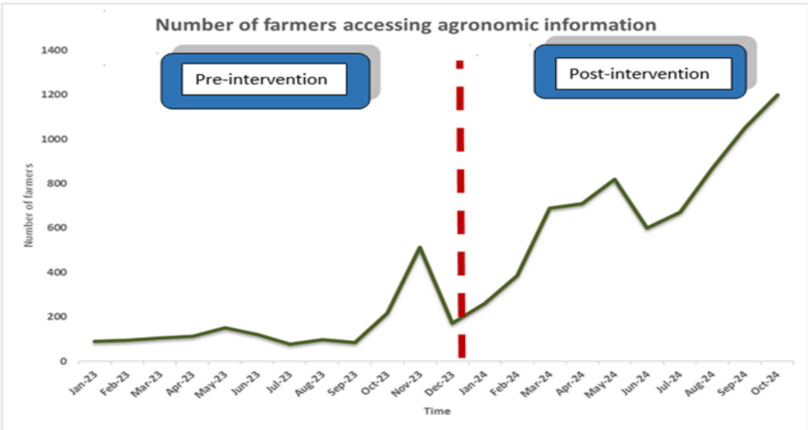
Figure 6: ***Use of EzyAgric platform***

We further provide a detailed breakdown of the population level services and information accessed via the EzyAgric platform following intervention in figure 7. The results from the EzyAgric database are further backed by those from the household survey (see figure 8).

Panel 1: Evolution of number of orders on EzyAgric platform



Panel 2: Number of farmers accessing agronomic information on EzyAgric platform



Panel 3: Evolution of the volumes ordered on EzyAgric platform

Figure 7: ***Population level service and information orders through the EzyAgric platform***

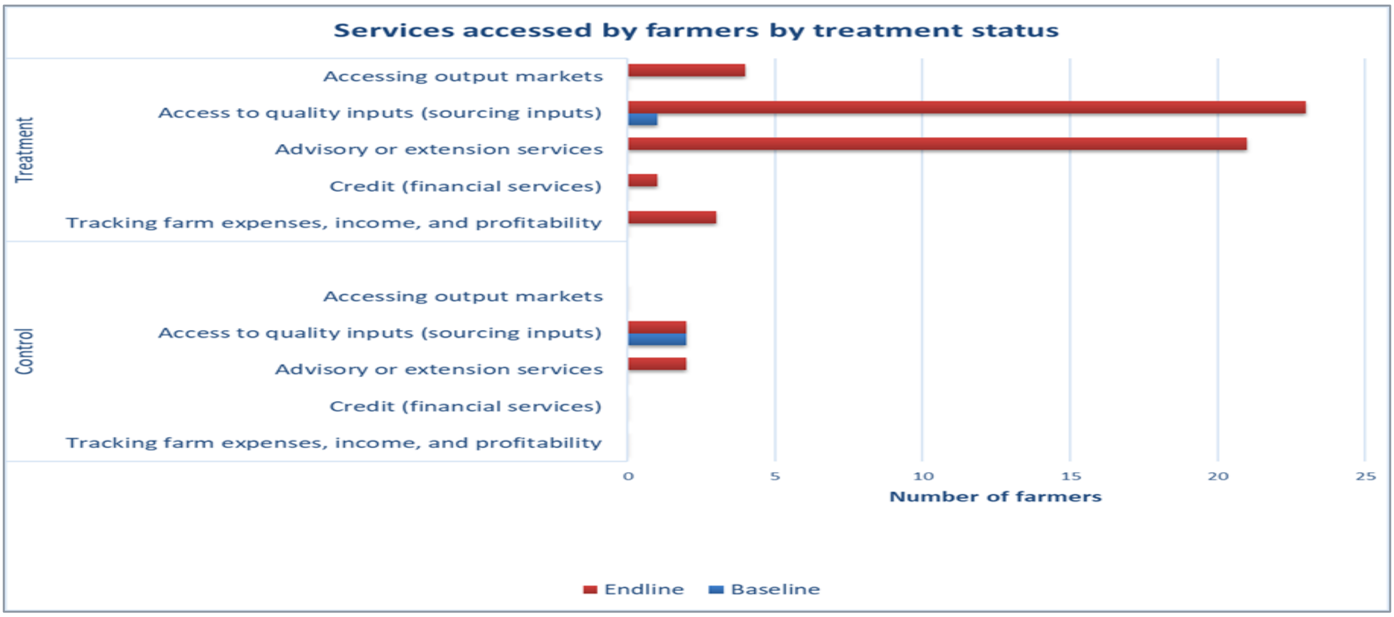
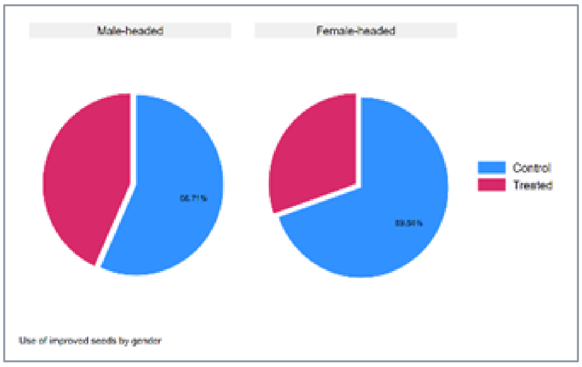
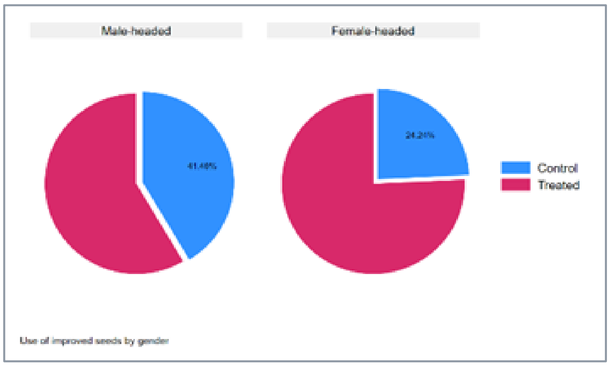


Figure 8: ***Survey level access to services on EzyAgric platform by treatment status***

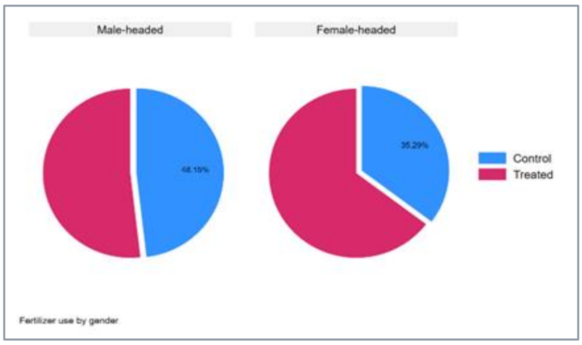
A cross examination of sex disaggregated agro-input use at household head level is displayed in figure 9. The results show that the proportion of men and women headed households using genuine and improved agro-inputs generally increased following the interventions, even though some marginal decrease can be observed for the proportion of male headed households using fertilizers following intervention.



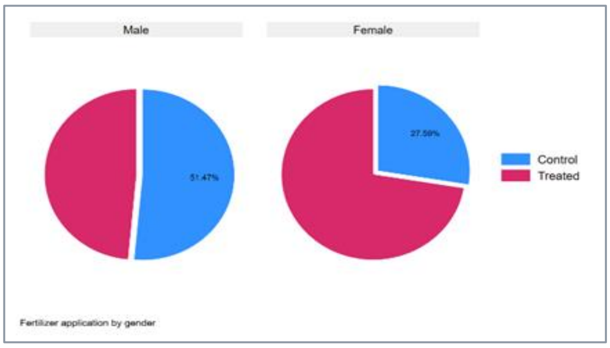
Panel 1: *Use of improved seeds by gender (baseline)*



Panel 2: *Use of improved seeds by gender (endline)*



Panel 3: *Fertilizer application by gender (baseline)*



Panel 4: *Fertilizer application by gender* (endline)

Figure 9: *Input use disaggregated by gender*

6.4. The impact of intervention on awareness

In this sub section, we examine the effect of the intervention on awareness of the EzyAgric platform using a linear probability model. The results show that the intervention created substantial awareness of the farmers on the EzyAgric digital platform. In particular, it resulted into about 30 percentage point increase in the awareness of the EzyAgric digital platform. Even though the overall results show a tremendous increase in awareness of the technology, older and aged subjects appear to have decreased awareness of the EzyAgric digital platform compared to the younger counter-parts.

Table 3: Probit model estimates of the impact of the intervention on awareness

Variables	**(1) Awareness**	**(2) Awareness**
Treatment effect	0.284*** (0.023)	0.297*** (0.023)
Female (1=Female, 0=Male)		-0.031 (0.033)
Age		-0.002** (0.001)
Education level		0.000 (0.001)
Household size (count)		0.008* (0.005)
Group member (Yes/No)		0.028 (0.027)
Farm size (acre)		0.001 (0.001)
Distance to village market (km)		0.006 (0.005)
Distance to agro-input dealer (km)		-0.002 (0.003)
Observations	1048	1048

Note: *Standard errors are in parentheses *** p<.01, ** p<.05, * p<.1, column 1 is the result of the regression including only the treatment*

The results also show that an increase in household size is associated with increased awareness of digital platforms. This could be because of enhanced information sharing avenues, given that the large household size could increase exposure to information access relating to the EzyAgric platform. For validation purpose we present linear probability estimates for this particular model in Table 3A.1 in the appendix

6.5. Agricultural inputs use and productivity indicators

6.5.1. Input use

In this section we present empirical results on the impacts of the intervention on application of agro-inputs such as fertilizers, genuine and improved seeds, and agro-chemicals (herbicides and fungicides). Table 4 presents the results of a parsimonious specification with only the intervention as a regressor. The results reveal positive and statistically significant effect of the awareness creation on improved seeds. In particular, there is a 14.7 percentage point increase in the use of improved seeds.

Table 4: Probit model estimates of treatment effects on input application

Variables	Improved seeds	Fertilizer	Agrochemicals
Treatment effect	0.147***	0.039	-0.148***
	(0.032)	(0.033)	(0.028)
Observations	1026	1026	1028

Note: *Standard errors are in parentheses *** p<.01, ** p<.05, * p<.1*

Adoption of innovative technologies such as genuine improved seeds holds enormous potential in increasing the productivity of smallholder farmers in Africa. However, the lack awareness of digital platforms that offer opportunities to enable access to genuine inputs such as improved seeds present a major constraint to their adoption. Bridging this gap through awareness creation is an effective means to boosting adoption. On the application of fertilizers, the empirical results reveal a positive but statistically insignificant relationship of the intervention and fertilizer application. Table 4 further reveals a negative and statistically significant impact on the application of agro chemicals. In a bid to encourage sustainable agricultural practices, efforts are made to reduce the application of agro chemicals. In the initial stages of the project, information and unawareness of the toxicity levels of agro-chemical inputs (herbicides, fungicides and pesticides) was one of the key problems in the intervention sites for which clarity was provided. Such inputs lead to environmental and human health hazards which the farmers got to know of and most likely led to the reduction in their use of these agro chemicals. Upon accounting for some of the baseline covariates, we find similar signs of influence of the intervention on input application as already reported in Table 4. There was however a slight increase in the magnitude of the use of improved seeds and a reduction for agro-chemical application. Increase in farm size was shown to increase uptake and application of improved seeds (see Table 5). Estimates using a linear probability model are displayed in Table 5A.1 attached in the appendices.

Table 5: Probit model estimates of treatment effects on input application (accounting for baseline covariates)

Variables	Improved seeds	Fertilizer	Agrochemicals
Treatment effect	0.163***	0.040	-0.134***
	(0.032)	(0.034)	(0.029)
Female (1=Female, 0=Male)	-0.052	0.018	-0.011
	(0.043)	(0.044)	(0.037)
Age (Years)	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Education level (years)	0.002*	0.001	0.000
	(0.001)	(0.001)	(0.001)
Household size(count)	0.004	-0.002	0.006
	(0.006)	(0.006)	(0.006)
Group member (Yes/No)	0.074**	0.022	0.042
	(0.035)	(0.036)	(0.030)
Farm size (acre)	0.003**	0.000	0.002
	(0.001)	(0.001)	(0.002)
Distance to village market (km)	-0.002	0.004	-0.006
	(0.007)	(0.007)	(0.006)
Distance to agro-input dealer (km)	0.000	0.001	0.005
	(0.004)	(0.004)	(0.003)
Observations	1026	1026	1028

Note: *Standard errors are in parentheses *** p<.01, ** p<.05, * p<.1*

6.5.2. Productivity indicators

Table 6 displays the results of the productivity impacts of the intervention on selected crops. In this study, the focus was on maize and beans as food crops and bananas and coffee as commercial/perennial crops. The estimated results reveal that there is no significant effect of the intervention on maize, banana and coffee yields. However, a negative and statistically significant effect is observed on bean yields. However, a positive trend is observed which could be an indication of emerging productivity gains that could result from the intervention.

Table 6: Treatment effect on productivity of selected crops

Variable	Maize yield	Beans yield	Banana yield	Coffee yield
	(kg/acre)	(kg/acre)	(bunches/acre)	(kg/acre)
Treatment effect	159.204	-653.372***	-25.171	55.456
	(242.735)	(205.817)	(28.475)	(34.175)
Constant	754.793***	1435.003***	104.106***	293.817***
	(173.282)	(150.014)	(21.456)	(24.699)
Observations	416.000	352.000	391.000	291.000
R-squared	0.001	0.028	0.002	0.009

Notes: *Standard errors are in parentheses; *** p<.01, ** p<.05, * p<.1*

When some baseline covariates are accounted for in Table 7, we still find no statistical significance for the treatment effects on maize, coffee and banana yields but bean yields remain negatively impacted. Regardless of these findings, we proceed to investigate the role some of these covariates. The empirical results reveal that individuals with group membership tend to have increased coffee yields compared to those who do not belong to any group. These results could probably be attributed to peer effect and the role it plays in disseminating useful agricultural production information that can be used to enhance yields.

Table 7: Treatment effect on productivity of selected crops (accounting for baseline covariates)

	(1)	(2)	(3)	(4)
Variables	**Maize yield**	**Beans yield**	**Coffee yield**	**Banana yield**
Treatment effect	470.192***	-629.059***	33.076	-52.364
	(122.128)	(199.57)	(45.67)	(59.794)
Pre-treatment maize yield	0.168*			
	(0.085)			
female	-67.224	-133.621	62.528	-7.793
	(107.088)	(221.013)	(68.602)	(34.342)
Age	-0.144	2.649	-1.945	-0.672
	(3.459)	(9.53)	(1.831)	(1.859)
education	-2.937	0.349	-0.732	0.817
	(2.492)	(5.492)	(2.264)	(1.09)
Household size	3.449	65.267	-8.074	-1.491
	(16.377)	(41.575)	(9.281)	(4.335)
Group member	46.319	492.239**	-42.102	-73.783
	(95.518)	(205.189)	(45.819)	(81.458)
Farm size	4.133	29.67	-4.516***	-1.975
	(3.057)	(21.257)	(1.396)	(3.901)
Distance to village market	-17.2	46.702	-1.309	-13.561
	(24.605)	(64.124)	(7.233)	(9.128)
Distance to agro-dealer	13.645	13.592	-6.666	-0.787
	(16.703)	(25.019)	(5.028)	(2.523)
Pre-treatment beans yield		-0.147		
		(0.93)		
Pre-treatment coffee yield			.072*	
			(0.038)	
Pre-treatment banana yield				0.044
				(0.089)
Constant	297.383	141.554	496.066***	256.077***
	(233.393)	(597.115)	(135.661)	(86.95)
Observations	284	197	158	204
R-squared	0.083	0.102	0.121	0.023

*Note: Outcome values are not transformed; Standard errors clustered at the village level are in parentheses; *** p<.01, ** p<.05, * p<.1*

6.5.3. Welfare indicators

This section presents results of the welfare impacts of EzyAgric digital awareness intervention on food and non-food expenditure per capita, gross production revenues and total value of assets. As can be observed from the empirical results in Table 8 below, the intervention had no statistically significant effect on all the four welfare outcome indicators tested. The coefficients for all the four welfare indicators are however positive. These results clearly give some indication of improvement in wellbeing of farmers who were exposed to the treatment. As Haughton and Khandker (2009) elegantly illustrate, the use of consumption indicators for welfare provides a better measure compared to indicators such as income that are highly volatile and prone to inaccuracies in developing economies.

Table 8: Treatment effects of awareness creation on expenditures per capita, gross production revenue and total value of assets

Variables	Food expenditure per capita	Non-food expenditure per capita	Gross production revenue	Total value of assets
Treatment effect	6.397	26523.832	1000615.3	174947.27
	(4.968)	(20015.895)	(1051272.3)	(1174619.2)
Pre-treatment food expenditure	0.369***			
	(0.119)			
Sex (1 = female, 0 = Male)	2.232	-28577.06	8706.515	-1997800.4*
	(8.153)	(21472.617)	(1397099.3)	(1022636.7)
Age	-0.044	-1553.222**	8512.265	-47026.003
	(0.151)	(674.499)	(20920.3)	(41717.64)
Education	-0.053	364.773	-18753.121	-31353.508
	(0.129)	(821.917)	(17964.024)	(19373.338)
Household size	-2.745***	-9060.006***	-211101.54	66182.454
	(0.997)	(3073.995)	(200984.38)	(141864.01)
Group member	1.624	3503.035	-340081.28	746505.3
	(5.285)	(17960.965)	(1174350.1)	(793393.29)
Farm size	-0.046	311.759	-8361.099	40033.61
	(0.058)	(271.89)	(10861.368)	(51973.284)
Distance to village mkt	-0.474	-6184.181*	-275843.46	-141816.83
	(1.008)	(3451.962)	(195617.85)	(281796.02)
Distance to agro-dealer	-0.403	-2526.843**	158225.34	-92669.281
	(0.455)	(1274.337)	(237782.89)	(81192.65)
Pre-treatment non-		0.048***		
food expenditure		(0.014)		
Pre-treatment gross			-0.004	
production revenue			(0.017)	
Pre-treatment value of				0.236**
assets				(0.099)
Constant	60.776***	325759.04***	6113714.3***	6001380.7***
	(11.849)	(43881.445)	(1744359.6)	(1949728.3)
Observations	498	501	486	501
R-squared	0.071	0.079	0.01	0.083

*Note: Outcome values are not transformed; Standard errors clustered at the village level are in parentheses; *** p<.01, ** p<.05, * p<.1*

The empirical results further show that the value of assets for farming households who were treated is on average 24 percentage points more than those in the control group. One interesting findings from our empirical estimations in Table 8 is the positive and statistical significance of the baseline values of our outcome variables. This implies that having higher values of these indicators enhances the follow-up values of these metrics.

7. Conclusions and policy implications

Limited access to genuine and improved inputs like seeds, agro-chemicals and agricultural advisory services present a major constraint to improving agricultural productivity in Sub-Saharan Africa. Often cited in the literature is the lack of information and knowledge in addressing these challenges. Given their lower cost effectiveness, digital innovations present enormous potential for addressing these challenges. However, adoption and use of digital innovations is often restricted due to information asymmetries, the lack of digital literacy and overall awareness of these technologies. Digital literacy and awareness creation campaigns could be leveraged to increase awareness and subsequent uptake and usage of digital innovations. However, the impacts of these interventions are rarely investigated in literature. In this study we use RCT to examine the effect of digital literacy and awareness creation campaigns on awareness, use and broader farm and household outcome indicators in Uganda.

The empirical results reveal that the intervention significantly increased awareness and use of EzyAgric innovations (services). We observe significant increase in uptake and use genuine and improved seeds. Interestingly, we find significant reduction in the use of agrochemicals following trainings on safe use and handing of agro-chemicals. Although we don't find significant effect of the interventions on crop productivity in the short run, the positive trend in consumption expenditure and total gross production revenues as well as the value of assets is promising and early indication to the benefits that await following uptake of the bundled digital innovations. These findings have policy implications as the initial empirical results show some positive semblance to inform mass scaling of digital innovations in Uganda.

8. Acknowledgments

This work is part of the CGIAR Research Initiatives on Rethinking Markets. CGIAR launched Rethinking Markets with national and international partners to leverage markets and value-chains to address nutrition, livelihoods, and environmental concerns in food systems, at national and subnational levels in seven countries in Africa, Asia, and Latin America. Other CGIAR centers participating in Rethinking Markets are: International Water Management Institute (IWMI), The Alliance of Bioversity International and the International Center for Tropical Agriculture (Alliance Bioversity-CIAT), International Institute of Tropical Agriculture (IITA), International Maize and Wheat Improvement Center (CIMMYT), International Center for Agricultural Research in the Dry Areas (ICARDA), and WorldFish. We would like to thank all funders who supported this research through their contributions to the CGIAR Trust Fund.

9. References

Abdulai, A. R., Quarshei, P. T., 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 & Food Policy*, *12*(11). https://doi.org/10.1186/s40066-023-00416-6

Alwang, J., Elisabetta, G., Graham, T., Guy, H., Moti, J., & Jordan, C. (2019). Pathways from Research on Improved Staple Crop Germplasm to Poverty Reduction for Smallholder Farmers. *Agricultural Systems*, *172*, 16–27.

Amadu, F. O., & McNamara, P. E. (2019). Performance incentives and information communication technologies in Ugandan agricultural extension service delivery. *African Journal of Food, Agriculture, Nutrition and Development*, *19*(1), 14113–14136. https://doi.org/10.18697/AJFAND.84.BLFB1007

Anderson, J. R. (2020). *"Agricultural Extension Policy: A 2020 re-Vision."* [Working Paper, Rutgers University Feed the Future Policy Research Consortium]. NJ. http://ru-ftf.rutgers.edu/Outputs%20for%20webpage/Anderson%20WP%202020.pdf

Ane, T., & Yasmin, S. (2019). Agriculture in the Fourth Industrial Revolution. *Ann. Bangladesh Agric*, *23*(2), 115–122.

Balyan, S., Jangir, H., Tripathi, S. N., Tripathi, A., Jhang, T., & Pandey, P. (2024). Seeding a Sustainable Future: Navigating the Digital Horizon of Smart Agriculture. *Sustainability*, *16*(475). https://doi.org/10.3390/su16020475

Baumüller, H. (2018). The Little We Know: An Exploratory Literature Review on the Utility of Mobile Phone-Enabled Services for Smallholder Farmers. *Journal of International Development*, *30*, 134–154. https://doi.org/10.1002/jid.3314

Birner, R., Daum, T., & Pray, C. (2021). Who drives the digital revolution in agriculture? A review of supply-side trends, players and challenges. *Appl Econ Perspect Policy*, *43*, 1260–1285.

Campenhout, B. V. (2021). The role of information in agricultural technology adoption: Experimental evidence from rice farmers in Uganda. *Econ. Dev. Cult. Change*, *69*, 1239–1272.

Choruma, D. J., Dirwai, T. L., Mutenje, M. J., Mustafa, M., Chimonyo, V. J. P., Jacobs-Mata, I., & Mabhadhi, T. (2024). Digitalisation in agriculture: A scoping review of technologies in practice, challenges, and opportunities for smallholder farmers in sub-Saharan Africa. *Journal of Agriculture and Food Research*, *18*(101286).

Das, S. (2023). Digitalization of Agriculture: Transforming Farming Practices for Sustainable Development. *Agriculture & Food. E-Newsletter*. http://www.agrofoodmagazine.co.in

Deichmann, U., Goyal, A., & Mishra, D. (2016). Will digital technologies transform agriculture in developing countries? *Agricultural Economics*, *47*(S1), 21–33. http://dx.doi.org/10.1111/agec.12300

DiTraglia, F. J., Garcia-Jimeno, C., O'Keeffe-O'Donovan, R., & Sanchez-Becerra, A. (2023). Identifying causal effects in experiments with spillovers and non-compliance. *Journal of Econometrics*, *235*, 1589–1629.

Erickson, B., & Fausti, S. W. (2021). The role of precision agriculture in food security. *Agronomy Journal*, *113*, 4455–4462.

Fafchamps, M., Asad, I., Mohammad, A. M., & Debayan, P. (2020). Can Referral Improve Targeting? Evidence from an Agricultural Training Experiment. *Journal of Development Economics*, *144*(102436). https://doi.org/10.1016/j.jdeveco.2019.102436

FAO, IFAD, UNICEF, WFP, & WHO. (2020). *The State of Food Security and Nutrition in the World 2020. Transforming food systems for affordable healthy diets*. Food and Agriculture Organization. https://doi.org/10.4060/ca9692en

Finger, R. (2023). European Review of Agricultural Economics. *Digital Innovations for Sustainable and Resilient Agricultural Systems*, *50*(4), 1277–1309.

Finger, R., Swinton, S., El Benni, N., & Walter, A. (2019). Precision farming at the nexus of agricultural production and the environment. *Annual Review of Resource Economics*, *11*, 313–335. http://dx.doi.org/10.1146/annurev-resource-100518-093929

Fitzgerald, J., Gottschalk, P., & Moffitt, R. (1998). An analysis of sample attrition in panel data: The Michigan panel study of income dynamics. *Journal of Human Resources*, *33*, 251–299.

Gerber, A. S., & Green, D. P. (2012). *Field Experiments: Design, Analysis and Interpretation*. W. N. Norton & company Inc.

Glennerster, R., & Takavarasha, K. (2013). *Running Randomized Evaluations: A Practical Guide*. Princeton University Press.

Hassani, M. S., Mohamed, H. I., Urassa, J. K., & Muhanga, M. I. (2023). Digital Literacy and Crop Productivity: Evidence from Cross-sectional Data in Hai and Moshi Districts, Kilimanjaro-Tanzania. *Tanzania Journal of Agricultural Sciences*, *22*(2), 264–279.

Ledermann, S. T., Anderson, J. R., & Pray, C. E. (2024). Observations on status and trends of agricultural extension and inequality in Uganda. *World Development Sustainability*, *4*(100147), 1–9.

Ligon, E., & Sadoulet, E. (2018). Estimating the Relative Benefits of Agricultural Growth on the Distribution of Expenditures. *World Development*, *109*, 417–428.

Ma, W., & Wang, X. (2020). Internet Use, Sustainable Agricultural Practices and Rural Incomes: Evidence from China. *Australian Journal of Agricultural and Resource Economics*, *64*, 1087–1112.

Magesa, M., Jonathan, J., & Urassa, J. (2023). Digital Literacy of Smallholder Farmers in Tanzania. *Sustainability*, *15*(13149). https://doi.org/10.3390/su151713149

Mckenzie, D. (2012). Beyond baseline and follow-up: The case of more T in experiments. *Journal of Development Economics*, *99*(2), 210–221.

Mirembe, D. P. (2021). Digitalisation of Agriculture in Africa: Challenges and Areas of Action. *RUFORUM Triennial Thought Pieces*, *09*. https://www.ruforum.org/Triennial2021/sites/default/files/RUFORUM%20Thought%20Pieces%202021_Issue%2009.pdf

Mirembe, D. P., Lubega, J. T., Ssekkkito, B., Nambogo, F., & Namagembe, B. (2023). Smallholder Farmer Access to ICTs and Digital Content: Experiences from Uganda. *African Journal of Rural Development*, *8*(1), 27–39.

Mirro, R. B., Luzobe, M., Mangheni, E., Asiimwe, & Owesigire, A. (2020). *"Responding to the COVID-19 lock down: AEAS actor experiences in Uganda: A survey by UFAAS" In "EXTENSION AND ADVISORY SERVICES: at the frontline of COVID-19 response for food security in Africa"*.

Pierpaoli, E., Carli, G., Pignatti, E., & Canavari, M. (2013). Drivers of precision agriculture technologies adoption: A literature review. *Procedia Technology*, *8*, 61–69.

Poushter, J. (2016). Smartphone Ownership and Internet Usage Continues to Climb in Emerging Economies. *Pew Research Center*, *22*, 1–5.

Rotz, S., Duncan, E., Small, M., Botshener, J., Dara, R., Mosby, I., Reed, M., & Fraser, E. D. G. (2019). The Politics of Digital Agricultural Technologies: A Preliminary Review. *Sociologia Ruralis*, *59*(2), 203–228.

Runck, B. C., Joglekar, A., Silverstein, K., Chan-Kang, C., Pardey, P., & Wilgenbusch, J. C. (2022). Digital agriculture platforms: Driving data-enabled agricultural innovation in a world fraught with privacy and security concerns. *Agronomy Journal*, *114*, 2635–2643.

Rwamigisa, P. B. (2020). *How can agricultural advisory services use digital tools to support farmers during the crisis? A perspective from Uganda*. ICABR. https://icabr.net/wp-content/uploads/2020/08/Rwamigisa_Impact-of-COVID-19_on_Extension_in_Uganda_ICABR_Webinar_July31_2020-1.pdf

Shang, L., Heckelei, T., Gerullis, M. K., Börner, J., & Rasch, S. (2021). Adoption and diffusion of digital farming technologies—Integrating farm-level evidence and system interaction. *Agricultural Systems*, *190*(103074). https://doi.org/10.1016/j.agsy.2021.103074

Singh, N. K., Sunitha, N. H., Tripathi, G., Saikanth, D. R. K., Sharma, A., Jose, A. E., & Mary, M. V. K. J. (2023). Impact of Digital Technologies in Agricultural Extension. *Asian Journal of Agricultural Extension, Economics & Sociology*, *41*(9), 963–970.

Trienekens, J. H. (2011). Agricultural value chains in developing countries a framework for analysis. *International Food and Agribusiness Management Review*, *14*(030-2016–82778), 51–82. https://doi.org/10.22004/ag.econ.103987

Tsan, M., Totapally, S., Hailu, M., & Addom, B. K. (2019). *The Digitalization of African Agriculture Report 2018–2019. CTA*. Technical Center for Agriculture and Rural Cooperation (CTA). https://www.cta.int/en/digitalisation-agriculture-africa

Tummers, J., Kassahun, A., & Tekinerdogan, B. (2019). Obstacles and features of farm management information systems: A systematic literature review. *Computers and Electronics in Agric*, *157*, 189–204.

Williamson, H. F., & Hartley, S. (2024). Responsible development of digital livestock technologies for agricultural challenges: Purpose, practicality and effects are key considerations. *Sociologia Ruralis*, 1–23.

World Bank. (2023). *Digital Acceleration Project – Implementation Status & Results Report*. https://documents1.worldbank.org/curated/en/099112624053031108/pdf/P17337316df8dc0a518b0c13b4a6f6e3c94.pdf

10. Appendix

Table 1A.1: Agro-input use indicators by treatment status

Variable	Pooled Sample	Control	Treated	Abs. Mean Diff.	Observations (N)
Improved seed used (dummy)	0.854	0.854	0.855	0.001	536
	(0.012)	(0.017)	(0.016)	(0.023)	
Inorganic Fertilizer. (Yes/No)	0.649	0.661	0.638	0.023	536
	(0.020)	(0.029)	(0.028)	(0.041)	
Organic Manure (Yes/No)	0.580	0.484	0.666	0.182***	536
	(0.021)	(0.031)	(0.028)	(0.042)	
Pesticides (Yes/No)	0.813	0.822	0.804	0.017***	536
	(0.016)	(0.024)	(0.023)	(0.033)	
Fungicides (Yes/No)	0.121	0 .133	0.109	0.023	536
	(0.014)	(0.021)	(0.018)	(0.028)	
Herbicides (Yes/No)	0.740	0.826	0.663	0.163***	536
	(0.018)	(0.023)	(0.028)	(0.037)	
Tractor/Oxen (Yes/No)	0.004	0.035	0.046	0.010	536
	(0.002)	(0.011)	(0.012)	(0.017)	
Obs	536	254	282		

Table 1A.2: Productivity indicators by treatment status

Variables	Pooled sample	Control	Treated	Mean difference	N
Panel A : Produced output					
Household-level					
Value of total production ('0,000 UGX)	944.487	1019.897	874.664	145.232*	520
	(41.680)	(59.020)	(58.5843)	(83.259)	
Obs	520	250	270		
Maize yield (kg/acre)	583.269	485.395	682.817	197.421**	236
	(45.511)	(57.878)	(69.489)	(90.303)	
Obs	236	119	117		
Coffee yield (kg/acre)	916.2265	1090.785	724.910	365.874	262
	(123.799)	(195.012)	(146.068)	(247.294)	
Obs	262	137	125		
Banana yield (bunches/acre)	383.262	423.556	343.481	80.075	312
	(55.448)	(94.992)	(58.014)	(110.984)	
Obs	312	155	157		
Panel B: Sold output					
Household-level					
Value of total sales ('0,000 UGX)	719.258	821.871	626.504	195.367***	535

	(30.782)	(45.929)	(40.657)	(61.118)	
Obs	535	254	281		
Maize sales (kg/acre)	1,226.08	687.859	1,735.76	1047.901*	257
	(310.201)	(138.332)	(587.2669)	(618.375)	
Obs	257	125	132		
Coffee sales (kg/acre)	961.7264	1200.490	693.381	507.108*	240
	(136.128)	(227.129)	(132.456)	(271.308)	
Obs	240	127	113		
Banana sales (bunches/acre)	122.387	102.9847	146.006	43.0215	357
	(15.258)	(20.377)	(22.938)	(30.622)	
Obs	357	196	161		

Table 1A.3: Well-being indicators by treatment status

Income	Pooled Sample	Control	Treated	Abs. diff.	N
Household income per annum ('0,000UGX)	1,346.86 (1,279.20)	1,475.30 (1,299.62)	1231.18 (1251.57)	244.12**	536
Income per capita per annum ('0,000 UGX)	256.75 (365.07)	276.92 (400.82)	238.59 (329.25)	38.33	536
Household has no cash income (%)	0.01	0.01	0.01	0.00	536
Consumption expenditures					
Household consumption expenditures per annum (UGX)	5,916,129 (526,399.7)	5,139,421 (436,425.6)	6,606,226 (914,314)	1,466,805 (1,053,697)	525
	536	254	282		
Consumption expenditures or per capita	983,430.8 (90659.02)	888,850 (122,039.3)	1,067,465 (132,499.5)	178,614.7 (181,640.7)	525
	536	254	282		
Asset					
Asset Index (score)	2.764	2.617	2.927	0.309***	536
	(0.049)	(0.071)	(0.066)	(0.097)	
	536	254	282		
Value of all assets (UGX)	4,918,822	4,324,836	5,567,237	1,242,401	525
	(591,664.3)	(762,237.8)	(915,912.2)	(1,184,352)	

Note: Values in parentheses are standard errors. *, ** and *** denote significance at 10, 5 and 1% respectively; Exchange rate in November 2023: USD 1 = UGX 3,785

Table 3A.1 Linear probability model estimates of the impact of the intervention on awareness

Variables	**(1) Awareness**	**(2) Awareness**
Treatment effect	0.288*** (0.025)	0.297*** (0.026)
Female (1=Female, 0=Male)		-0.024 (0.033)
Age		-0.001 (0.001)
Education level		0.000 (0.001)
Household size (count)		0.008 (0.005)
Group member (Yes/No)		0.030 (0.027)
Farm size (acre)		0.001 (0.001)
Distance to village market (km)		0.006 (0.006)
Distance to agro-input dealer (km)		-0.001 (0.003)
Constant	0.097*** (0.018)	0.059 (0.053)
Observations	1048	1048

Note: *Standard errors are in parentheses *** p<.01, ** p<.05, * p<.1, column 1 is the result of the regression including only the treatment*

Table 5A. 1 Linear probability model estimates of treatment effects on input application (accounting for baseline covariates)

Variables	Improved seeds	Fertilizer	Agrochemicals
Treatment effect	0.159***	0.042	-0.138***
	(0.034)	(0.034)	(0.029)
Female (1=Female, 0=Male)	-0.057	0.018	-0.015
	(0.044)	(0.044)	(0.038)
Age (Years)	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Education level (years)	0.002*	0.001	0.000
	(0.001)	(0.001)	(0.001)
Household size(count)	0.005	-0.002	0.005
	(0.006)	(0.006)	(0.006)
Group member (Yes/No)	0.071**	0.022	0.044
	(0.036)	(0.036)	(0.031)
Farm size (acre)	0.002**	0.000	0.001
	(0.001)	(0.001)	(0.001)
Distance to village market (km)	-0.002	0.003	-0.006
	(0.007)	(0.007)	(0.006)
Distance to agro-input dealer (km)	0.000	0.001	0.005
	(0.004)	(0.004)	(0.003)
Constant	0.358***	0.648***	0.744***
	(0.070)	(0.070)	(0.060)

Observations	1026	1026	1028

Note*: Standard errors are in parentheses *** p<.01, ** p<.05, * p<.1*

Table 7A. 1 DID estimates with untransformed crop yield values (No covariates included)

	(1)	(2)	(3)	(4)
	maize_yield	win_beans_yield	banana_yield	win_coffee_yield
Trt_Status	-78.28	-9.497	17.476	-23.437
	(59.561)	(15.134)	(36.909)	(88.267)
Time	-225.559	1278.989***	-153.24***	-270.43***
	(187.469)	(173.792)	(38.177)	(61.403)
did	164.009	-643.875***	-42.648	78.893
	(200.866)	(198.155)	(47.378)	(94.269)
Constant	829.393***	156.014***	257.346***	564.247***
	(36.515)	(9.593)	(25.197)	(58.92)
Observations	882	632	659	545
R-squared	.002	.118	.082	.048

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 7A. 2 DID estimates with untransformed crop yield values (Covariates included)

	(1)	(2)	(3)	(4)
	maize_yield	win_beans_yield	banana_yield	win_coffee_yield
	-45.708	114.695***	10.257	-28.364
	(63.161)	(34.628)	(38.32)	(86.578)
	-216.182	1321.568***	-155.036***	-266.09***
	(193.084)	(175.536)	(38.101)	(60.209)
	154.602	-725.161***	-38.58	84.162
	(204.248)	(196.562)	(48.474)	(94.102)
	-111.317	-250.227***	25.751	33.073
	(68.82)	(78.972)	(25.976)	(56.835)
	-4.044	-3.489**	-.629	-4.248**
	(3.263)	(1.472)	(.982)	(1.906)
	-1.136	-2.075	.034	-1.676**
	(2.549)	(2.431)	(.68)	(.751)
	-13.437	52.516	-1.635	.649
	(10.184)	(37.084)	(3.245)	(10.026)
	58.274	-39.015	-50.035*	-80.918
	(98.626)	(125.914)	(26.78)	(49.722)
	-1.545	12.728***	-.785	-3.158*
	(1.362)	(3.336)	(.494)	(1.698)
	-19.625	12.153	-8.192**	-1.429
	(13.46)	(26.666)	(3.422)	(7.205)
	17.036*	-1.425	1.402	.562
	(8.849)	(7.427)	(1.6)	(4.486)
	1100.344***	-91.735	349.704***	871.872***
	(173.244)	(275.14)	(59.108)	(136.93)
	882	632	659	545
	.008	.155	.094	.078

Table 7A. 3 DID estimates with transformed crop yield values (No covariates included)

	(1) trans_maize_yield	(2) trans_beans_yield	(3) trans_banana_yield	(4) trans_coffee_yield
Trt_Status	-.229**	-.059	-.016	.209
	(.105)	(.121)	(.217)	(.306)
time	-2.022***	1.679***	-1.641***	-.151
	(.198)	(.122)	(.196)	(.301)
did	.202	-.798***	.126	.221
	(.283)	(.168)	(.301)	(.407)
_cons	7.152***	5.32***	5.278***	5.558***
	(.06)	(.078)	(.137)	(.212)
Observations	882	632	659	545
R-squared	.136	.203	.165	.007

*Note: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1*

Table 7A. 4 DID estimates with transformed crop yield values (Covariates included)

	(1) trans_maize_yield	(2) trans_beans_yield	(3) trans_banana_yield	(4) trans_coffee_yield
Trt_Status	-.092	.039	-.063	.146
	(.115)	(.122)	(.226)	(.304)
time	-1.982***	1.715***	-1.644***	-.162
	(.194)	(.121)	(.194)	(.306)
did	.143	-.851***	.151	.297
	(.278)	(.167)	(.309)	(.413)
female	-.453*	-.089	.32*	.104
	(.235)	(.116)	(.186)	(.217)
age	-.013***	-.008***	-.008	-.016**
	(.003)	(.002)	(.005)	(.007)
Education	-.002	-.001	.005	-.002
	(.007)	(.005)	(.007)	(.005)
Household size	.031	.049**	.021	.01
	(.033)	(.021)	(.025)	(.042)
Group member	-.275	.169	-.163	.018
	(.181)	(.126)	(.15)	(.223)
Farm size	.002	.008***	-.01*	-.024***
	(.003)	(.002)	(.005)	(.006)
Distance to village market	.004	.021	-.01	.013
	(.035)	(.019)	(.025)	(.032)
Distance to agro-input dealer	.013	0	.025*	.002
	(.015)	(.012)	(.013)	(.014)

Constant	7.802***	5.148***	5.601***	6.475***
	(.32)	(.212)	(.326)	(.499)
Observations	882	632	659	545
R-squared	.154	.233	.184	.056

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 7A.5. ANCOVA estimates with transformed crop yield values (Covariates included)

	(1) Maize yield	(2) Beans yield	(3) Coffee yield	(4) Banana yield
Treatment effect	.072	-.727***	.178	-.422
	(.322)	(.208)	(.363)	(.275)
Pre-treatment maize yield	-.022			
	(.143)			
female	-.635	-.056	.311	.269
	(.427)	(.265)	(.375)	(.364)
Age	-.012	-.009	-.016	-.015
	(.01)	(.009)	(.013)	(.01)
education	-.01	.006	-.001	.009
	(.01)	(.006)	(.007)	(.011)
Hhsize	.022	.133***	-.02	-.022
	(.065)	(.038)	(.055)	(.045)
Group member	-.022	.415*	.005	.331
	(.328)	(.236)	(.329)	(.276)
Farm size	.002	.024**	-.013	-.048*
	(.012)	(.01)	(.01)	(.026)
Distance to village mkt	-.014	.074*	.02	-.069
	(.068)	(.039)	(.07)	(.065)
Distance to agrodealer	-.019	.015	-.059	.002
	(.031)	(.026)	(.056)	(.034)
Pre-treatment beans yield		-.02		
		(.083)		
Pre-treatment coffee yield			.081	
			(.08)	
Pre-treatment banana yield				.008
				(.078)
Constant	6.25***	5.939***	6.321***	5***
	(1.336)	(.723)	(.934)	(.812)
Observations	346	197	158	204
R-squared	.016	.197	.063	.069

*Note: Outcome values are transformed using inverse hyperbolic sine; Standard errors clustered at the village level are in parentheses; *** p<.01, ** p<.05, * p<.1*

Table 8A. 1 DID estimates with transformed welfare indicator values (Covariates included)

	(1)	(2)	(3)	(4)
Variables	**trans_foodexp_perc~a**	**trans_nonfoodexp_p~a**	**trans_gross_pdnrev~e**	**trans_asset_value**

Trt_Status	-.015	-.099	-.214	-.167
	(.103)	(.109)	(.167)	(.144)
did	.168	.278**	.606	.272*
	(.142)	(.133)	(.755)	(.157)
time	.169*	-1.522***	-7.887***	-.08
	(.093)	(.097)	(.566)	(.102)
female	-.026	-.122	-.244	-.437***
	(.067)	(.095)	(.438)	(.135)
age	.001	-.002	-.007	.004
	(.001)	(.002)	(.007)	(.003)
educ	.002	-.001	.016	-.005
	(.002)	(.003)	(.01)	(.004)
hhsize	-.066***	-.031**	.06	.051**
	(.013)	(.014)	(.065)	(.023)
group_member	.082	.135*	-.273	.349***
	(.066)	(.079)	(.409)	(.118)
farm_size	.002**	.004***	.012	.014***
	(.001)	(.002)	(.014)	(.005)
dist_village_mkt	-.011	-.023	-.007	-.045
	(.014)	(.023)	(.076)	(.033)
dist_hse_agro	0	-.019	-.005	.017
	(.007)	(.016)	(.039)	(.015)
_cons	4.496***	14.305***	16.495***	14.231***
	(.144)	(.18)	(.633)	(.252)
Observations	1034	1037	1022	1037
R-squared	.061	.286	.305	.079

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Table 8A.2. ANCOVA estimates with transformed welfare indicator values (Baseline covariates included)

	(1) Food expenditure per capita	(2) Non-food expenditure per capita	(3) Gross production revenue	(4) Total value of assets
Treatment effect	.141	.181	.313	.129
	(.097)	(.125)	(.808)	(.151)
Pre-treatment food expenditure	.121**			
	(.046)			
female	-.033	-.078	-.419	-.348***
	(.106)	(.114)	(.896)	(.129)
Age	-.002	-.01**	-.009	-.001
	(.003)	(.004)	(.014)	(.005)
education	0	0	.026	-.007***
	(.002)	(.005)	(.023)	(.002)
Hhsize	-.036	-.036**	.048	.019
	(.022)	(.018)	(.133)	(.02)

Group member	.027	-.09	-.574	.159
	(.104)	(.095)	(.837)	(.119)
Farm size	.001	0	.01	.001
	(.001)	(.002)	(.025)	(.003)
Distance to village mkt	-.005	-.001	.014	-.026
	(.021)	(.033)	(.156)	(.037)
Distance to agrodealer	-.015	-.051	-.047	-.03
	(.013)	(.032)	(.081)	(.023)
Pre-treatment non-food expenditure		.161***		
		(.05)		
Pre-treatment gross production revenue			.023	
			(.263)	
Pre-treatment value of assets				.518***
				(.059)
Constant	4.233***	11.215***	8.664*	7.235***
	(.278)	(.738)	(4.622)	(.833)
Observations	498	501	486	501
R-squared	.041	.09	.006	.262

*Note: Outcome values are transformed using inverse hyperbolic sine; Standard errors clustered at the village level are in parentheses; *** p<.01, ** p<.05, * p<.1*

Sylvester Ogutu (s.o.ogutu@cgiar.org) is a Postdoctoral Fellow, Enoch Kikulwe (e.kikulwe@cgiar.org), a Senior Scientist, Susan Ajambo (s.ajambo@cgiar.org), an Associate Scientist and Eliud Birachi (e.birachi@cgiar.org), a Project Leader at Alliance Bioversity-CIAT. Stewart Ategeka (stewartategeka@ezyagric.com) is Project manager at EzyAgric.

We would like to thank all funders who support this research through their contributions to the CGIAR Trust Fund: www.cgiar.org/funders.

To learn more about this Initiative, please visit this webpage.

To learn more about this and other Initiatives in the CGIAR Research Portfolio, please visit www.cgiar.org/cgiar-portfolio

CGIAR

INITIATIVE ON
Rethinking
Food Markets