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Digital Literacy Training to Promote Diffusion of Digital Agricultural Tools to Smallholder Farmers

Evidence from a Randomized Intervention in Egypt

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Abstract

Despite growing enthusiasm about the potential of digital innovations to transform agrifood systems, adoption among smallholder farmers in Africa remains low and heterogeneous. While the proliferation of digital tools targeting smallholder farmers is encouraging, the vast majority remain at pilot stages, facing important demand and supply-side barriers to adoption. This paper evaluates alternative digital literacy interventions designed to address these demand-side barriers. Following a Training of Trainers (TOT) model, we designed and implemented a randomized control trial to test three variants of digital literacy training: standard classroom-based digital literacy training (T1), digital training complemented (preceded) by a video-based play (T2), digital training complemented (preceded) by a live community play (T3), and a control group (C). We find that all variants of digital training significantly increased the uptake and utilization of digital tools by smallholder farmers. Specifically, the standard digital training alone increased uptake by 20 percentage points and utilization by 26 percentage points. The interventions also significantly enhanced farmer trust in digital tools by 8–13 percentage points. Surprisingly, for some outcomes, the digital literacy training alone outperformed the combined approaches that incorporated edutainment nudges. We explore possible explanations, including group size effects and social influence dynamics during the plays. We also document heterogeneity in the impact of these interventions across farmers' gender and age. Our findings offer insights for designing cost-effective and scalable interventions to build digital capabilities and trust among smallholder farmers.

Keywords: Smallholder farmers, technology adoption, digital agriculture, digital literacy, edutainment

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1. Introduction

There is growing enthusiasm on the potential of digital innovations to facilitate agricultural transformation and improve the functioning of markets by addressing multiple forms of institutional and market failures (e.g., Courtois and Subervie, 2015; Aker et al., 2016; Spielman et al., 2021; Aker and Cariolle, 2023; Abate et al., 2023a). Digital innovations have been widely recognized for their ability to address information asymmetry across market actors, reducing transaction costs and ultimately increasing market participation (Abate et al., 2023a; Zhao et al., 2019; Spielman et al., 2021). This is likely to be more evident in remote areas, where digital tools such as mobile phones and their associated applications can be used to address various aspects of fixed transaction costs such as search, negotiation, and bargaining costs. While the rapid spread of mobile phones and their integration into farming systems present a unique opportunity to transform smallholder agriculture in low- and middle-income countries (Aker, 2011; Fabregas et al., 2019; Singh et al., 2023; Aker and Cariolle, 2023),[1] the adoption of digital tools among smallholder farmers in Africa remains far below expectations, leaving substantial untapped potential across the region. The landscape of digital innovations in Africa is also marked by a persistent digital divide (Mehrabi et al., 2021). Less than 40 percent of smallholder households have access to the internet, and access increases with farm size (Mehrabi et al., 2021). Marginalized farmers—particularly women, those with lower education levels, and poorer households—face even greater barriers of access to digital technologies. These barriers include lower mobile phone ownership, limited digital literacy, and social and cultural constraints (Abu-Shanab, 2015; Cole and Fernando, 2021; Mehrabi et al., 2021; Steinke et al., 2024).

In Egypt, the focus of this study, uptake of these technologies remains low despite the increasing and considerable investment and availability of digital agricultural tools. Egyptian smallholder farmers often lack awareness about the benefits of digital tools and can be easily excluded from this agricultural digital revolution. The failure of many digital innovations to scale and sustain adoption raises fundamental questions about the barriers preventing smallholder farmers from fully integrating digital tools into their agricultural practices and highlights an

[1] The opportunity becomes more pronounced as numerous efforts and initiatives in Africa have resulted in the emergence of various digital innovations aimed at connecting buyers and sellers, improving price transparency, and addressing information asymmetries between farmers and traders (Tabe-Ojong et al., 2024).

interplay between supply-side and demand-side constraints (Mehrabi et al., 2020; Abate et al., 2023a).

Among demand-side barriers, low digital literacy, particularly among older farmers and those in remote areas, is commonly cited as an important constraint limiting the use of digital agricultural applications (Abate et al., 2023a; Tabe-Ojong et al., 2024). Even when digital solutions are available, farmers frequently encounter usability and accessibility barriers, stemming from technical complexity or poor interface design (Tabe-Ojong et al., 2024). Similarly, user confidence and trust in digital tools remain an underexplored yet crucial factor in shaping adoption outcomes (Aker, 2016; Abate et al., 2023a; Giulivi et al., 2023; Fabregas et al., 2025). Growing evidence suggests that skepticism toward digital platforms is not solely due to inaccessibility but rather a result of familiarity bias and distrust in digital tools (Fabregas et al., 2019; Tabe-Ojong et al., 2024; Fabregas et al., 2025).

Focusing on demand-side barriers, this study evaluates the effectiveness of alternative methods of delivering digital literacy trainings to raise smallholders' knowledge, utilization, trust, and uptake of two Egyptian agricultural apps that provide marketing and agricultural advisory services. The digital literacy training approach we implement builds on the Training of Trainees (TOT) model, where 30 local trainees from farmer communities, first trained by digital application developers themselves, are tasked with training other farmers in their communities. To ensure that TOTs are sufficiently incentivized, we designed trainers' incentives to be a function of the number of farmer trainees who pass a digital literacy test.[2] Once the TOT concluded and our trainers were ready, we proceeded to combine two complementary interventions: (i) digital-literacy training delivered by TOTs in classrooms to farmers, and (ii) edutainment "nudges" delivered through short videos or a live community play. The *digital literacy training* component is designed to address digital illiteracy and raise awareness about existing digital tools, providing farmers with the foundational skills needed to effectively navigate them. The *edutainments* serve as additional nudges designed to increase the attractiveness and saliency of the digital literacy training. This builds on recent evidence about the potential and role of *edutainment* to support conventional trainings. We deliver our *edutainment* through two forms: short videos or live community plays. Recent studies in Uganda (Van Campenhout, 2021) and Nigeria (Bello-Bravo et al., 2018) show

[2] Conventional training has not been as effective as needed, especially when in-person trainings deployed to farmers are not complemented by other nudging tools like SMS texts, calls, or interactive media (Abate et al., 2023b).

that complementary videos effectively communicated agronomic information to farmers, noting that adding an animated video to a training facilitated group discussions and led to higher knowledge and uptake. Following these studies, we complement some of the digital trainings through additional videos demonstrating practical encounters and experience with digital tools. Similarly, the community play aims to foster greater interest, boost training engagement, and ultimately build trust in digital tools. The community play was added to test whether its salient nature can encourage farmers to participate in the digital literacy training and hence facilitate learning and adoption of digital innovations. Considering these variations, we evaluated these modalities in a four-arm randomized controlled trial: standalone digital literacy training (T1), digital training preceded by a video-based play (T2), digital training preceded by a live community play (T3), and a pure control group (C).

The results show that all three variants of the digital training significantly improved smallholder farmers' knowledge, uptake, and utilization of digital agricultural tools. For example, the digital training on its own (T1) led to a 20–percentage point increase in uptake and adoption of digital tools. We also find that the alternative digital literacy trainings increased trust in digital agricultural tools by 8–13 percentage points. While adding edutainment elements (T2 and T3) increased the intensity of utilization, improved farmer perceptions of the tools' relevance, and increased trust, digital literacy training alone (T1) outperformed the combined approaches for some of the outcomes.

Our findings imply that hands-on trainings that can enhance digital skills and actively engage farmers may offer more immediate and scalable solutions to closing the digital divide in smallholder agriculture. Grounded in social-learning theory, our design explores whether emotional engagement through edutainment can foster trust in and adoption of digital tools, as opposed to traditional, cognitive-based training methods. While edutainment can generate immediate interest, its long-term efficacy in shifting deeply ingrained behaviors is still debated (Grady et al., 2021; Cole and Fernando, 2021; Peterman, 2025). Our findings contribute evidence on how different nudge strategies influence trust, usability, and sustained adoption of digital agricultural tools. By addressing skepticism and the reluctance to adopt new technologies, important barriers often become evident among marginalized farming communities, our intervention design offers practical insights into how digital training, coupled with edutainment, can serve as a behavioral nudge and facilitate adoption of digital tools. The findings in this paper highlight the potential of cost-effective digital literacy trainings to facilitate adoption of digital tools in low- and middle-income contexts. The size of the impacts we document, combined with the low cost of the digital literacy training, offers critical lessons for policymakers and development practitioners seeking to promote and sustain the uptake of agricultural digital innovations.

2. Review of Existing Literature

2.1. The landscape of digital tools in Africa

Several studies highlight the potential of digital platforms to amplify market participation and engagement in agribusiness by facilitating rapid and efficient information dissemination (for example, Zhao et al., 2019; Spielman et al., 2021).[3] Empirical evidence highlights the positive impacts of digital tools on farmers' profits and marketing outcomes, demonstrating their capacity in matching agricultural supply with market demand (Birner et al., 2021; Abate et al., 2023a). Other studies illustrate how information communication technology (ICT) platforms can facilitate real-time price monitoring and hence access to market and agronomic advisory support (Aker, 2011; Van Campenhout, 2017, Fabregas et al., 2019; Singh et al., 2023). More specifically, digital innovations can improve the functioning of markets by (i) reducing communication and information costs; (ii) improving farmers' knowledge and know-how about market options and prices; (iii) improving access to input and output markets; (iv) overcoming enforcement challenges by reducing uncertainty, risk, and the costs of monitoring and enforcing transactions in imperfect markets; (v) facilitating the delivery of other services associated with agricultural markets such as credits and finance; (vi) improving management of input and output supply chains; and (vii) strengthening communication and mutual trust among market stakeholders.

Adoption of digital tools among smallholder farmers across Africa remains low and uneven, and agricultural markets remain fragmented, underdeveloped, and constrained by persistent inefficiencies (Abate et al., 2023a; Aker and Cariolle, 2023). Although numerous digital solutions targeting smallholders emerged over the past decade, the vast majority remain in pilot stages, with limited evidence of successful scaling or transformative impact on agricultural markets. Cases where digital innovations have successfully scaled and driven measurable impacts

[3] For example, in Colombia, Iacovone, and McKenzie (2019) show that the adoption of digital tools by farmers had enhanced the value chain efficiency of fruits and vegetables by providing farmers an avenue to circumvent middlemen and unnecessary transaction costs.

remain restricted to specific sectors and contexts (Fabregas et al., 2019; Abate et al., 2023a; Aker and Cariolle, 2023). This is compounded by the persistent digital divide—fewer than 40 percent of smallholder households have access to the internet, and access increases with farm size (Mehrabi et al., 2021).

These broader trends are similarly observed in Egypt, where smartphone ownership is notably higher among urban households (81 percent) than rural households (68 percent) (ICT Indicators Bulletin, 2022).[4] Barriers such as fragmented markets, limited rural connectivity, and pronounced gender and educational disparities further constrain digital participation (Alozie and Akpan-Obong, 2017; Fatehkia et al., 2018). Marginalized groups, particularly women and less-educated farmers, and poorer households, face even greater barriers to accessing digital technologies. Lower mobile phone ownership, limited digital literacy, and cultural constraints disproportionately affect these groups (Cole and Fernando, 2021; Mehrabi et al., 2021; Steinke et al., 2024). Empirical evidence from several contexts shows that lower-educated and women farmers are the least likely to adopt and use ICT-based services and have been found to benefit more from traditional extension channels than from digital formats (for example, Giulivi et al., 2022). This is ironic, especially given the presumption that digital tools may generate greater impact among marginalized smallholders. Understanding these persistent gaps in digital adoption requires examining both supply-side infrastructural constraints and demand-side behavioral challenges.

2.2. Supply-side versus demand-side barriers

Given these persistent challenges, an important debate about whether low adoption rates are driven predominantly by supply-side failures or demand-side constraints emerges. It is not obvious which side can explain the empirical disconnect between successful pilots and limited scale-up of digital innovations (Mehrabi et al., 2020; Abate et al., 2023a). Supply-side barriers largely consist of structural challenges related to the broader technological ecosystem in which smallholder farmers operate. Key obstacles include limited mobile network coverage, inadequate internet access, and unreliable electricity supplies (Aker and Cariolle, 2023). Limited investment in complementary infrastructure, particularly in rural and marginalized regions, restrict access to digital services.

[4] This survey named "ICT usage in households and individuals" was conducted by the Ministry of Communications and Information Technology (MCIT) in cooperation with the Central Agency for Public Mobilization and Statistics (CAPMAS), 2021–2022.

Furthermore, the high cost of internet data plans and smartphones disproportionately affects poorer farmers, further exacerbating the digital divide (Mehrabi et al., 2020; Singh et al., 2023). Even when farmers gain access to digital platforms, unsustainable business models, characterized by high service costs and poor scalability, frequently prevent the long-term viability of these tools (Abate et al., 2023a; Birner et al., 2021).

On the other hand, demand-side barriers stem from the socioeconomic, behavioral, and cognitive barriers that influence farmers' decisions to adopt digital tools. A primary challenge is low digital literacy, particularly among older farmers and those in remote areas who often struggle to navigate the interfaces of mobile applications (Aker et al., 2016; Abate et al., 2023a). Technical complexity, poor interface designs, and usability issues further discourage engagement (Tabe-Ojong et al., 2024) as well as cultural barriers and gender norms associated with how women engage with technology (e.g., Alozie and Akpan-Obong, 2017; Fatehkia et al., 2018). Trust and user confidence in digital tools, though underexplored, emerge as critical determinants of adoption.(Aker, 2016; Abate et al., 2023a; Giulivi et al., 2023; Fabregas et al., 2025). Growing evidence suggests that skepticism toward digital platforms is not solely due to inaccessibility but rather a result of familiarity bias and distrust in digital tools (Fabregas et al., 2019; Tabe-Ojong et al., 2024; Fabregas et al., 2025). Farmers accustomed to face-to-face interactions with traders and trusted intermediaries may view unfamiliar digital alternatives with caution, particularly when concerns about reliability or fraud and misinformation may arise (Cole and Fernando, 2021; Giulivi et al., 2022; Fabregas et al. 2025).[5] Without targeted efforts to design inclusive digital services that account for literacy, access barriers, and local contexts, digital agriculture interventions risk reinforcing inequality and further widening the existing digital divide (Steinke et al., 2024).

2.3. Strategies to promote adoption of digital agricultural tools

Previous studies have deployed and tested alternative interventions to promote adoption of digital agricultural tools. Nudging strategies are frequently employed to encourage smallholder farmers to adopt agricultural technologies (Spielman et al., 2021; Van Campenhout, 2021; Abate et al.,

[5] In addition, cognitive biases and short-term decision-making tendencies can discourage farmers from investing in unfamiliar technologies despite their long-term benefits. In many cases, farmers need social validation or peer influence to feel confident in adopting new technologies, reinforcing the role of community-driven adoption processes (Spielman et al., 2021; Fernando, 2021).

2023a). However, there is limited empirical evidence on which types of demand-side interventions are most effective for farmers with low digital literacy. Low-cost nudges, such as SMS reminders and voice messages may raise awareness, but their effectiveness in driving sustained behavioral change and improvements in agricultural productivity outcomes remains mixed (Cole and Fernando, 2020; Fabregas et al., 2025; Spielman et al., 2021; Abate et al., 2023b). This aligns with broader literature indicating that knowledge dissemination alone is often insufficient to achieve meaningful behavioral shifts, especially among farmers with limited digital experience (Balew et al., 2023; Spielman et al., 2021; Dzanku et al., 2022).

To address this, some studies suggest that edutainment-based approaches, such as videos and media strategies, may outperform purely informational campaigns by leveraging emotional engagement and social learning (Singhal et al., 1993). There are several mechanisms through which edutainment can drive behavior change, including through narrative persuasion, social modeling, and emotional resonance (Singhal et al., 1993; La Ferrara, 2016; Grady et al., 2021). This suggests that edutainment may effectively overcome issues related to digital literacy and trust by presenting information in a relatable, engaging, and accessible manner, thereby facilitating behavioral change. Edutainment approaches have been widely used in various contexts to bring about change at the community level.[6] Some studies have explored the use of videos and interactive media to educate farmers about pest management, crop diseases, and sustainable farming practices (Bello-Bravo et al., 2018; Grady et al., 2021; Van Campenhout, 2021), noting that adding an animated video to a training facilitated group discussions and led to higher knowledge and uptake. Other studies employed more complex edutainment strategies such as radio series, television campaigns, and role-playing games to foster social learning and collective action, and promote agricultural innovation diffusion (Singhal and Rogers, 1993; Heong et al., 2008; Singhal and Rogers, 2012; Salvini et al., 2016). Findings from recent studies show that visually engaging formats significantly improve retention, motivation, and understanding of complex agricultural practices compared to audio-only or non-interactive methods (Van Campenhout, 2021; Dzanku et al., 2022; Abate et al., 2023b).

[6] Beyond agriculture, edutainment tools have been widely used to tackle topics such as family planning, adult literacy, domestic violence, and public health, among others (Vaughan et al., 2000; Singhal and Rogers, 2012; Peterman, 2025).

Nevertheless, the depth and durability of edutainment's impacts continue to raise debates. Some evidence indicates that while edutainment generates short-term interest and participation, its long-term effectiveness in altering deeply ingrained behaviors remains uncertain (Grady et al., 2021; Cole and Fernando, 2021; Peterman, 2025). Other studies suggest that edutainment interventions must be complemented by follow-up support and reinforcement to be effective and sustainable (Peterman, 2025). Consequently, the effectiveness of dissemination strategies depends significantly on not only what information is delivered but also on the mode of delivery, making this a critical consideration for both policy and practice (Dzanku et al., 2022). Building on this literature, we introduced targeted digital literacy trainings alongside edutainment nudges to assess their impacts on the uptake of digital agricultural tools in Egypt.

3. Context, Data, and Descriptive Statistics

3.1. Context and target population

The target population of the study are smallholder farmers located in two governorates in Upper Egypt—Minya and Benisuef—which are the geographical focus of the Agricultural Innovation Project (AIP) of the German Corporation for International Cooperation (GIZ). Minya is an agricultural governorate located in northern Upper Egypt with 75 percent of its population of 6 million working in agriculture. The estimated cultivated area is 500 thousand feddans,[7] and most of this land is cultivated with different strategic crops including wheat, sugar cane, sugar beet, corn, potatoes, medicinal and aromatic plants, fava beans, and export crops such as grapes and garlic—all of which are irrigated from Al-Ibrahimia and Bahr Yusef canals through a group of sub-canals (SIS, 2022). Minya has a desert fringe in the west, covering an area of about 150 thousand feddans, with new areas for agriculture reclaimed as part of recent governmental projects. The governorate has about 200 agricultural cooperatives, which provide support to farmers, including financial assistance, training, and marketing services (FAO, 2020).

Benisuef is a governorate located about 120 kilometers (km) south of Cairo on the west bank of the Nile River, with a population of approximately 4 million. The total cultivated area is approximately 320,000 feddans in 2022 (Youm7, 2022), and the main crops cultivated include medicinal and aromatic plants, clover, cotton, wheat, sugarcane, fava beans, and vegetables. The governorate has a history of producing quality crops for export such as chamomile, potatoes,

[7] *Feddan* is a unit of area commonly used in Egypt and other countries in the Middle East and North Africa. One feddan is the equivalent of 0.42 hectares, or approximately 1.038 acres.

onions, and garlic, hence the governorate has recently been a candidate for government projects dedicated to improving irrigation systems, such as the expansion of modern drip irrigation systems to increase productivity and enhance the quality of crops for export. Most Benisuef industries are related to agriculture, including flour milling, drying and processing of medicinal and aromatic plants, cotton ginning, and textile manufacturing (El Shrouk News, 2023).

Traditionally, Egyptian smallholder farmers rely heavily on limited and often suboptimal advisory and market channels to conduct their businesses. With government scale-backs of extension services and shortages in agricultural extension personnel, many farmers have little access to professional agronomic advice (Swelam et al., 2022). As a result, smallholder farmers turn to more traditional channels like local input dealers or informal peer networks, but their recommendations can be biased, outdated, or poorly suited to address farmers' real and context-specific needs, limiting their ability to make well-informed decisions. Farmers also depend on intermediaries and traders to market their produce; these actors frequently hold monopsony power, manipulating prices through storage control or commission fees, thereby eroding farmers' profit margins. These traditional channels also contribute to high transaction costs, including time spent searching for trustworthy inputs and negotiating prices, which ultimately diminish farmers' ability to connect with broader markets (IFAD, 2008; Jouanjean, 2019; GIZ, 2020).

Agricultural digital tools in Egypt, such as Mahsoly and Cropsa, have the capacity to directly address these challenges. Mahsoly's price-monitoring feature provides farmers with real-time, farm-gate price data, empowering them to bypass exploitative intermediaries and negotiate better deals. Additionally, it allows farmers to advertise and sell their produce in an open, transparent market. Cropsa complements this by offering reliable advisory content, ranging from pest diagnostics to trusted input supplier information, reducing farmers' dependence on unreliable sources and enhancing decision-making transparency (Tabe-Ojong et al., 2024). By consolidating access to trustworthy agronomic advice and transparent market information via smartphone apps, these digital tools can reduce information asymmetries, lower transaction costs, and enhance farmers' profitability and market participation.

3.2. Data and descriptive statistics

A baseline phone survey was conducted between July and September 2023, targeting 4,000 farmers across Minya and Benisuef. These farmers come from a database belonging to GIZ's Agricultural Innovation Project (AIP). After excluding those whose primary occupation was not farming, the resulting sample comprised 3,332 farmers. Table 1 provides an overview of the baseline demographic and household characteristics of the farmers surveyed by phone. Essentially half (49 percent) of the farmers interviewed are from Benisuef and the remaining half (52 percent) are from Minya. Most farmers interviewed are male (85 percent), with an average age of 45 years. The average household size is approximately 6. Based on self-reported literacy, about 65 percent of farmers had completed at least primary school, and approximately 35 percent reported having no formal education. Over half of the farmers (57 percent) reported owning land, while 40 percent of the sample reported owning livestock that generated additional agricultural income. In terms of crops, nearly all farmers (91 percent) plant wheat, while 56 percent also plant clover.

Table 1: Farmers' demographic and household characteristics

Household Characteristics	Mean	Std. Dev.
Governorate (share)		
Benisuef	0.488	0.500
Minya	0.512	0.500
Age (years)	44.575	13.026
Male (0/1)	0.846	0.361
Household size (#)	5.667	2.56
Education category (share)		
No education	0.352	0.48
Primary	0.05	0.22
Secondary	0.067	0.25
Post-secondary	0.532	0.499
Land ownership	0.574	0.495
Livestock ownership	0.60	0.49
Involved in wheat cultivation	0.907	0.29
Involved in clover cultivation	0.548	0.498
Number of observations	3,332	

Source: Authors' calculations based on (baseline) household data.

3.3. Constraints to adoption of digital agricultural tools

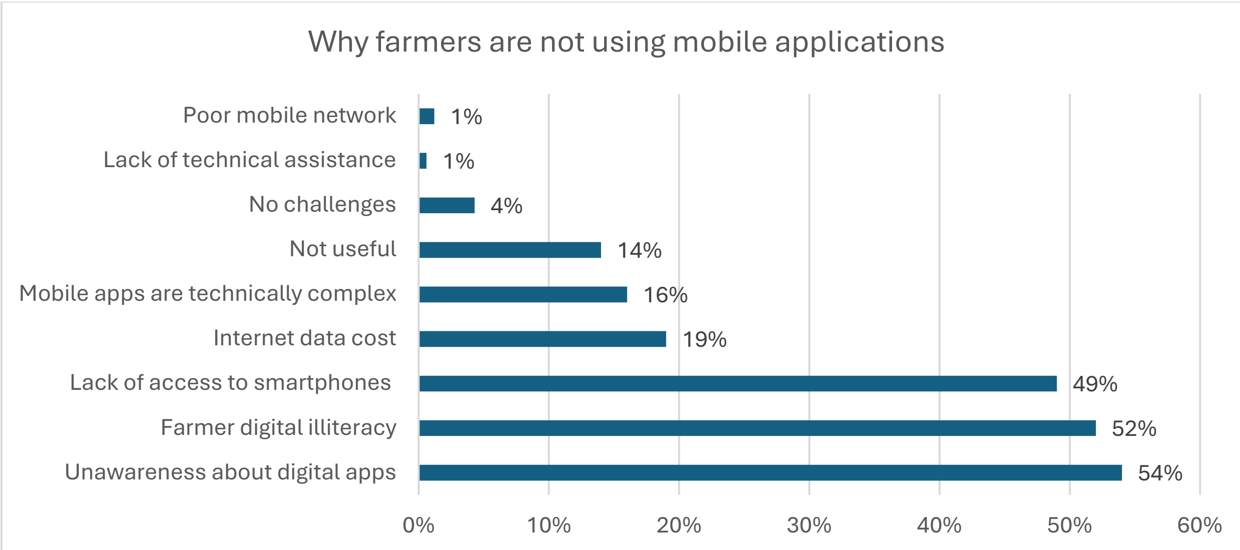
To understand the landscape of digital infrastructure (including mobile phone ownership and access to internet) in Minya and Benisuef, farmers were asked to report on their access to these infrastructures. Given that most digital agricultural apps require smartphones, we elicit ownership of ordinary phones and smartphones. Baseline survey findings reveal that the majority of farmers

(97 percent) own a mobile phone, whereas only 72 percent own a smartphone (See Figure A1 in Appendix A). When revisiting this analysis by farm size, it appears that medium and large farm holders are more likely to own a smartphone (79 percent) than smallholders (64 percent) (See Figure A2 in Appendix A).

Moreover, when it comes to internet access, farmers were asked to report on both home internet data and mobile data. Survey findings indicate that only 33 percent of farmers have access to home internet data, while a larger sample (47 percent) have some access to mobile data (25 percent of which have regular access). Similarly, analyzing this by farm size shows that farmers with a larger farm size have better and more regular access both to home internet (41 percent compared to 26 percent) and to mobile data (30 percent compared to 18 percent) (See Figure A3 in Appendix A).

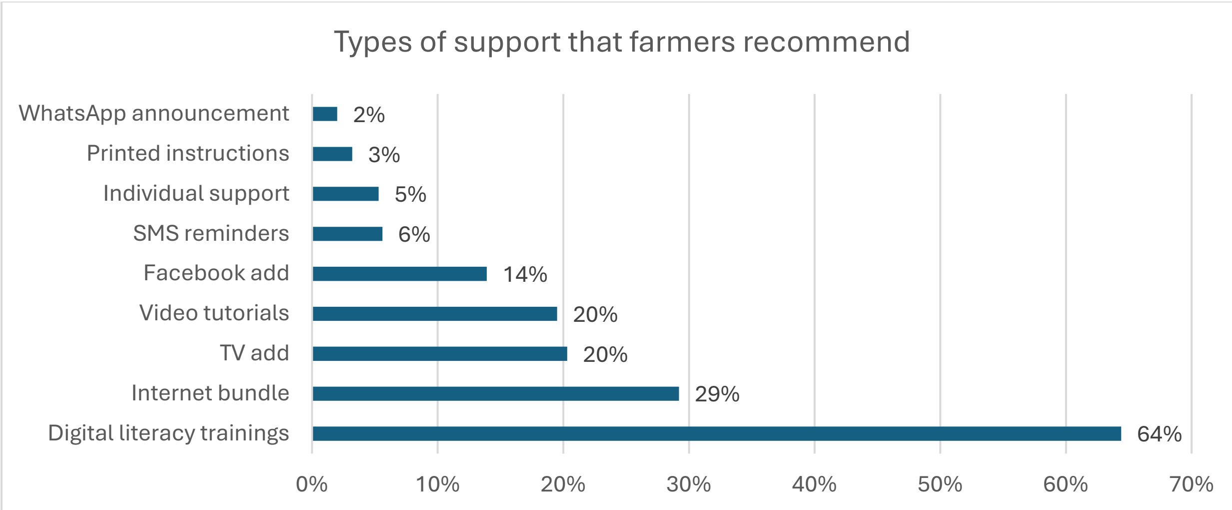
While these common infrastructural challenges impact farmers' access to digital tools, they are not the only obstacles farmers face in effectively utilizing digital tools. Figure 1 delves deeper into additional challenges farmers face in adopting and utilizing digital tools. The majority of the sampled farmers cited that the main obstacle is simply lack of awareness about the different existing digital applications (54 percent), and a similar majority (52 percent) reported that general digital literacy is a key challenge. Furthermore, sampled farmers reemphasized the lack of access to smartphones as a common challenge, with at least half of them (49 percent) identifying it as a key obstacle. The high cost of internet (19 percent), the complexity of mobile applications (16 percent), and the lack of usefulness of mobile applications (14 percent) were also reported reasons as to why farmers are not using digital applications. These results align with the challenges similarly identified in the literature (see section 2.2).

Figure 1: Major challenges why farmers are not using mobile applications



These findings provided a foundation and starting point for the design of the interventions outlined in this project to promote the use of digital tools to smallholder farmers and enhance their access to and understanding of these tools. To address the challenges above, farmers were asked to provide their recommendations on how best to address these barriers. As illustrated in Figure 2, the majority of farmers (approximately 64 percent) identified digital literacy training as a solution. When analyzing this by gender, it appears that women farmers (74 percent) were more interested in digital literacy trainings than male farmers (65 percent). The second most identified solution was to provide access to subsidized internet bundles (30 percent). These insights supported the research team's choice of interventions, which largely focused on launching digital literacy trainings to farmers and equipping the sessions with free internet access during the trainings to facilitate farmers' learning and utilization of the different digital applications.

Figure 2: Types of support that farmers recommend to improve adoption of digital tools



4. Intervention and Experimental Design

4.1. Intervention

The intervention evaluated in this study is part of the GIZ's Agriculture Innovation Project (AIP), which aims to enhance the uptake of digital agricultural tools among smallholder farmers in Minya and Benisuef through tailored educational interventions and innovative promotional strategies.[8] The specific focus of our intervention in this study is on two mobile applications: Mahsoly and Cropsa. Mahsoly assists farmers in advertising and selling their crops and lands, provides location-specific crop prices, and includes weather forecasting services. Cropsa enables farmers to access agricultural input shops, offers advisory services for crop diseases, and facilitates payment for inputs through separate installments or cash, along with delivery options.

Of the 3,332 farmers included in our baseline survey, 2,400 farmers had access to smartphones and thus formed the primary study sample. These 2,400 farmers were randomly assigned to either one of three treatment groups or a control group as follows: (i) standalone digital literacy training (T1), (ii) digital training preceded by a video-based community play (T2), (iii) digital training preceded by a live community play (T3), and a pure control group (See Figure 3). Three promotional strategies were carefully designed and implemented in collaboration with local farmer organizations (FOs) to assess how effectively they promoted the two mobile apps. Below is a description of these interventions:

[8] This research experiment was preregistered with the American Economic Association's RCT Registry (AEARCTR-0012723), and the design and implementation followed the specifications outlined in the pre-analysis plan (PAP).

(i). Digital literacy training through Training of Trainees (TOT) sessions: This intervention focused on structured, instruction-based training designed around the use of Mahsoly and Cropsa. Initially, 30 trainers of trainees (TOTs) from Minya and Benisuef were recruited and received specialized training directly from the developers of the digital apps, following a standardized curriculum.[9] These TOTs then held training sessions with farmers over two months, and each session accommodated up to 20 farmers in existing FO facilities. Training sessions included hands-on, practical demonstrations on how to download, navigate, and effectively utilize these digital applications. To incentivize effective training, trainers' remuneration was directly linked to farmer learning outcomes, specifically the number of farmers passing a digital literacy and knowledge test. Trainers were compensated only after administering this test to trained farmers, marking a significant departure from conventional training incentive models.

(ii). Digital literacy training through Training of Trainees (TOT) sessions plus pre-recorded community play video: This training variant incorporated a pre-recorded community play video designed to nudge farmers about digital agricultural tools in an engaging, entertaining format. The play's script humorously illustrated typical market barriers and trader-related challenges that smallholder farmers encounter, with characters promoting digital tools as essential solutions for overcoming these constraints. The pre-recorded play was screened to farmers immediately before their digital literacy training session in the same training facility, thus enhancing engagement and framing the subsequent training content.

(iii). Digital literacy training through Training of Trainees (TOT) sessions plus live community play: The third intervention variant offers a more salient nudge, where we invite farmers to a live, theater-style community play hosted in tents across six different communities in Minya and Benisuef to ensure wide outreach. The scripts in the pre-recorded community play and the live community play are exactly the same, but the latter is presented live with a larger audience capped at 100 farmers per play. One week following the live performance, farmers were invited to participate in the standard TOT digital literacy training session at their local FO, reinforcing the messages introduced during the play.

[9] The TOT was provided over a two-day period in a workshop format. This two-step model—where (1) app developers train TOTs, and (2) TOTs train farmers—enabled the rapid rollout of training across multiple communities without relying on external facilitators for every session.

Figure 3: Study design

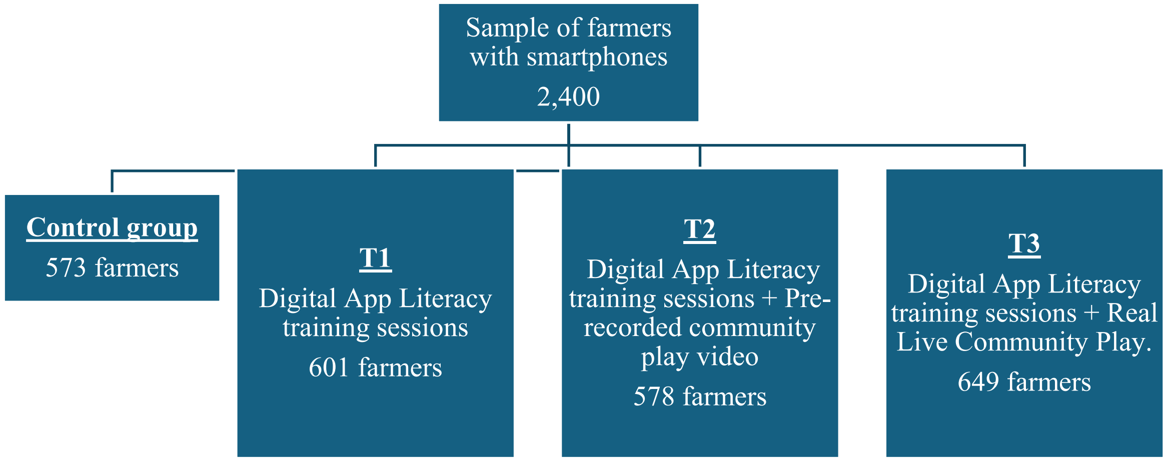


Table 2 provides descriptive evidence on compliance and attrition rates among the different groups. The compliance rate was computed using self-reported information on actual participation in the training sessions.[10] The patterns show comparable rates of compliance as well as attrition across the different groups.

[10] This may be susceptible to some level of misreporting by farmers, although we expect such sources of misreporting to be uncorrelated with the treatment assignment.

Table 2: Compliance and attrition rates

Panel A: Compliance rates			
Treatment Assignment	**Sample**	**Complied to Treatment**	**Treatment Compliance Rate**
(T1) Training only	601	468	78%
(T2) Training + Video	578	462	80%
(T3) Training + Live Play	649	481	74%
Control	573	489	86%

Panel B: Attrition rates			
Treatment Assignment	**Baseline**	**Follow-up**	**Survey Attrition Rate**
(T1) Training only	601	564	6%
(T2) Training + Video	578	540	7%
(T3) Training + Live Play	649	615	5%
Control	573	539	6%
Total sample	2,401	2,258	6%

Source: Authors' calculations based on (baseline and follow-up) household data.

4.2. Balance tests

We tested for balance across treatment assignments by considering a comprehensive list of observable characteristics measured at baseline to probe whether the demographic and socioeconomic characteristics of farmers are similar across the control and three treatment arms. This helps to test validity of the randomization. Table 3 below shows that most of the observable characteristics are balanced across all arms.

4.3. Follow-up survey

Following the baseline survey and about three-four months after the intervention, we conducted a follow-up phone survey and revisited the same farmers. As reported in Table 2, we managed to re-interview 94 percent of the farmers included in the baseline survey. More importantly, the 6 percent attrition rate appears to be comparable across the four study arms.

Table 3: Balance of observable characteristics of farmers

Variable	(1) T1 Mean/(SE)	(2) T2 Mean/(SE)	(3) T3 Mean/(SE)	(4) Control Mean/(SE)	(1)-(2) t-test (p-value)	(1)-(3) t-test (p-value)	(1)-(4) t-test (p-value)	(2)-(3) t-test (p-value)	(2)-(4) t-test (p-value)	(3)-(4) t-test (p-value)
Respondent Educational Attainment	5.50	5.46	5.34	5.48	0.78	0.44	0.91	0.62	0.86	0.50
	(0.16)	(0.14)	(0.17)	(0.14)						
Household Size	5.80	5.81	5.87	5.79	0.97	0.66	0.92	0.66	0.88	0.47
	(0.14)	(0.12)	(0.12)	(0.15)						
Land Owned	0.64	0.61	0.62	0.60	0.30	0.41	0.10*	0.69	0.80	0.47
	(0.02)	(0.03)	(0.03)	(0.03)						
Number of Feddans Owned	2.15	2.03	2.01	2.62	0.72	0.72	0.30	0.96	0.13	0.21
	(0.28)	(0.26)	(0.31)	(0.37)						
FO Service Satisfaction	2.78	2.73	2.71	2.68	0.45	0.34	0.22	0.80	0.40	0.60
	(0.05)	(0.05)	(0.06)	(0.06)						
Access to Market Information	0.60	0.58	0.65	0.63	0.50	0.08	0.19	0.00	0.09	0.53
	(0.02)	(0.02)	(0.02)	(0.03)						
Access to Internet	0.45	0.47	0.46	0.43	0.69	0.70	0.42	0.88	0.27	0.22
	(0.02)	(0.03)	(0.02)	(0.02)						
Access to Mobile Internet	0.64	0.66	0.63	0.65	0.52	0.55	0.85	0.20	0.59	0.42
	(0.02)	(0.02)	(0.02)	(0.02)						
Access to Social Media	0.65	0.66	0.62	0.63	0.94	0.18	0.45	0.16	0.30	0.58
	(0.02)	(0.02)	(0.02)	(0.02)						
Access to Finance	0.33	0.31	0.32	0.26	0.38	0.46	0.02	0.81	0.02	0.03
	(0.02)	(0.03)	(0.02)	(0.03)						
Access to Market	0.87	0.85	0.85	0.88	0.18	0.18	0.73	0.94	0.17	0.06
	(0.02)	(0.02)	(0.02)	(0.02)						
Livestock Ownership	0.61	0.60	0.59	0.57	0.82	0.54	0.23	0.83	0.24	0.57
	(0.03)	(0.03)	(0.03)	(0.03)						
Digital App Use	0.12	0.09	0.10	0.10	0.17	0.38	0.29	0.59	0.55	0.99
	(0.02)	(0.01)	(0.02)	(0.01)						
Awareness of Mahsoly App	0.17	0.20	0.19	0.17	0.16	0.47	0.92	0.65	0.27	0.61
	(0.02)	(0.02)	(0.02)	(0.02)						
Download of Mahsoly App	0.04	0.03	0.04	0.03	0.50	0.92	0.35	0.54	0.69	0.40
	(0.01)	(0.01)	(0.01)	(0.01)						
Intensity of Digital App Use	0.08	0.06	0.08	0.08	0.25	0.93	0.67	0.20	0.40	0.61
	(0.02)	(0.01)	(0.01)	(0.01)						
Perception on App Usefulness	0.11	0.09	0.10	0.10	0.31	0.48	0.39	0.67	0.72	0.95
	(0.02)	(0.01)	(0.01)	(0.01)						
Recommend Use of Digital Apps	0.85	0.87	0.84	0.88	0.47	0.55	0.12	0.14	0.35	0.01***
	(0.02)	(0.02)	(0.02)	(0.02)						
Trust Digital Apps	0.75	0.78	0.75	0.80	0.28	0.87	0.03**	0.28	0.25	0.04**
	(0.02)	(0.02)	(0.02)	(0.02)						

Note: This table reports results of a balance test across different pairs of comparisons. Values out of parentheses represent mean values while those inside parentheses stand for standard errors.
Source: Authors' calculations based on (baseline) household data.

5. Empirical Strategy

As expected, farmers in the control and the treatment groups are statistically comparable in terms of their observable and unobservable characteristics. Random assignment ensures that unbiased estimates of the impact of the offer of treatment can be computed using simple mean comparisons. However, as reported in Table 2, not all farmers assigned to the treatment attended the trainings, implying imperfect compliance. For this purpose and following our pre-analysis plan, we follow the random assignment of farmers into the three treatment groups (T1, T2, and T3) and control group to estimate the intention-to-treat (ITT) effect. As we have baseline data for most outcome variables, we estimated a more saturated and powered difference-in-differences specification. We particularly estimate the following empirical equation using baseline and follow-up data:

$$Y_{it} = \alpha_i + \beta_1 R_t + \sum_{j=1}^{3} \beta_{2j} T_i^j * R_t + \varepsilon_{it} \qquad (1)$$

Where Y_{it} is an outcome of interest for farmer *i* measured at round *t*. As described above, we aim to identify the impacts of the digital literacy trainings on several outcomes, including: (i) knowledge of digital agricultural tools, (ii) utilization and relevance of digital agricultural tools for marketing purposes, (iii) trust and user confidence in digital tools, and (iv) uptake of digital agricultural tools. α_i represents individual/farmer fixed effects, which captures any time-invariant variation and unobserved heterogeneities across farmers (including impacts associated with factors such as gender). R_t is a time dimension, capturing a binary time fixed effect that assumes a value of zero at baseline, and 1 at follow-up. T_i^j is a categorical variable capturing the three treatment arms: (i) Digital Literacy, (ii) Digital Literacy + Pre-recorded Community Play, and (iii) Digital Literacy + Community Play. The third term in equation (1) captures the interaction effects across treatment and dummy rounds. We note these farmer fixed effects are perfectly correlated with the time-invariant treatment indicator and hence we are not controlling for T_i^j separately. ε_{it} captures additional unobservable factors that may affect our outcome of interest, which are expected to be uncorrelated with our treatment assignment.

The main parameters of interest in equation (1) are the vector of parameters contained in β_{2j}. These are the difference-in-differences estimates from the comparison of each treatment arm with the control group and before and after the intervention. Beyond quantifying the overall impact of the digital training compared to the control group, we are also interested in comparing the relative effectiveness of the three variants of digital literacy trainings. In other words, we aim to identify potential additional complementary impacts of the pre-recorded and actual community plays. Thus, the empirical specification in equation (1) allows us to identify the absolute and relative impact of each digital promotion strategy. For this purpose, we conduct pairwise comparisons of the sizes of these coefficients. For some outcomes we are missing baseline data. Thus, we adapt equation (1) and rely on the cross-sectional variation in exposure to the different types of promotional strategies and trainings.

We also explore potential heterogeneous effects across farmers by splitting the sample across different groups of farmers (for example, men versus women). We then implement equation (1) to each sample split. Such heterogeneity analyses are important to understand who benefits more from these digital literacy training and complementary edutainments. Farmers living in the same community are likely to face similar digital infrastructure and markets, which can generate a spatial correlation of unobserved effects (error terms) across farmers from the same community. Thus, we cluster standard errors at the village level, which is the smallest geographical unit in our sample.[11]

6. Results and Discussion

Below we report some descriptive results based on the baseline and follow-up surveys, mainly focusing on changes in: (i) knowledge of digital agricultural tools, (ii) utilization and relevance of digital agricultural tools for marketing purposes, (iii) trust and user confidence in digital tools, and (iv) uptake of digital agricultural tools. For each set of outcomes, we use alternative indicators.

6.1 Impacts on knowledge

We use two indicators to measure farmers' awareness and knowledge of digital tools, which were administered in the follow-up survey. Hence, our parametric results are estimated from a cross-sectional variant of equation (1). First, to evaluate the impact of the interventions on digital knowledge, we administered a short digital literacy test as part of the follow-up survey. Column (1) of Table 4 reports the impact of the different digital literacy trainings and promotional strategies

[11] In our robustness exercises, we also cluster standard errors at the farmer organization level, and we show that this does not change our main statistics inferences.

on farmers' digital literacy, measured by computing a digital literacy score comprised of correct farmer responses to five different digital literacy questions that capture farmers' ability to navigate the internet, download digital tools, share location and upload related crop information when utilizing a digital tool for farm purposes. The results in Table 4 suggest that the digital literacy trainings increased the digital literacy score by 0.28 points, equivalent to 9 percent improvement relative to the control mean. Similar studies that assess the impacts of training programs on farmers' overall knowledge and confidence report positive significant effects (Spielman et al., 2021; Abate et al., 2023b).

Second, a different test was administered to assess farmers' understanding, knowledge, retention, and familiarity associated with the two agricultural digital applications that they received direct training on (Mahsoly and Cropsa). The knowledge test score (Column 2 in Table 4) measures farmers' retention of key information about these apps three months after the training. The test consisted of 14 questions assessing farmers' understanding of app functionalities, benefits, and usage. Farmers' knowledge scores were calculated based on the number of correct responses to these questions. The knowledge test results in Column 2 show that T1 (Training only) yielded the highest average knowledge score, while T3 (Training + Community Play) resulted in the lowest effect. The p-values reported at the bottom of Table 4 indicate that we can reject the null hypothesis that these two treatment arms had similar effects on knowledge retention, pointing to a statistically significant difference between them.

To further analyze comprehension, we constructed a binary pass or fail indicator (Column 3 in Table 4), classifying farmers as having passed if they answered 6 or more of the 14 questions correctly. We note that the renumeration to the training of trainees was a function of the number of farmers who passed these tests. The estimates in Table 4 show that the digital literacy training session alone (T1) increased the likelihood that a farmer passes a digital knowledge test by up to 43 percentage points, while attending a community play before a digital literacy training (T3) increased the likelihood of passing a knowledge test by only 36 percentage points. Again, the p-value for the effects associated with T1 versus T3 comparison confirms that this difference is statistically significant, reinforcing the finding that farmers in T3 retained less information than those in T1. These results align with Grady et al. (2021), who argue that entertainment elements can sometimes overshadow key instructional content and lead to lower knowledge retention. It is possible that farmers in T3 remembered the storyline of the play but struggled to retain technical details about app functionalities, unlike those in T1, who received a focused training. Furthermore, as shown in the later sections of the paper, T3 sessions had significantly larger class sizes, which likely limited the trainer's ability to engage individually with farmers. Fewer opportunities for hands-on learning may have compromised learning outcomes. Overall, our findings suggest much larger knowledge gains compared to studies that rely on a bundle of passive nudging interventions. For instance, Lopez et al. (2023) reports only a 6–12 percentage point increase in farmer knowledge following their nudging interventions (messaging, videos, social media campaigns). This underscores the value of structured, in-person training over low-touch nudging approaches when the goal is deep knowledge transfer.

Table 4: The impact of different digital promotional strategies on farmer digital literacy

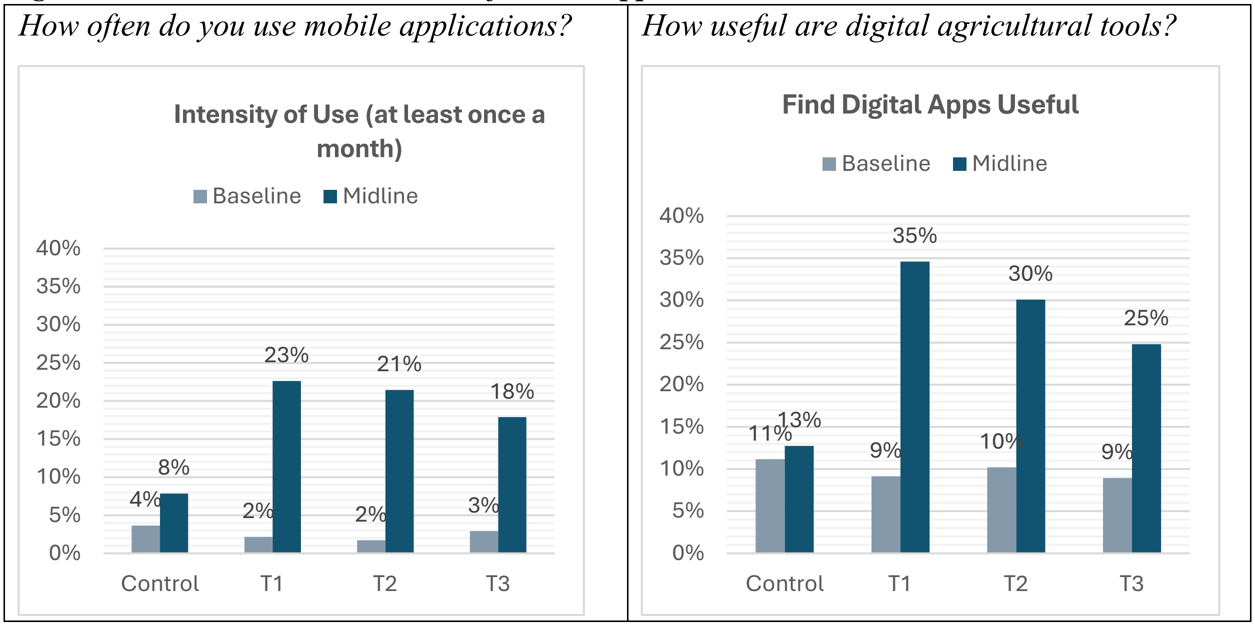
	(1) Digital Literacy Score	(2) Knowledge Test Score	(3) Passed Knowledge Test
(T1) Training only	0.276^{***}	4.098^{***}	0.429^{***}
	(0.109)	(0.285)	(0.031)
(T2) Training + Video	0.188^{***}	4.068^{***}	0.419^{***}
	(0.103)	(0.303)	(0.035)
(T3) Training + Play	0.211^{***}	3.556^{***}	0.366^{***}
	(0.114)	(0.238)	(0.025)
R-squared	0.003	0.116	0.123
Mean of the control group	2.981	2.315	2.981
Number of observations	2242	2258	2258
Pairwise t-test (p-value)			
T1=T2	0.397	0.918	0.674
T2=T3	0.842	0.166	0.213
T1=T3	0.619	0.097	0.089

Note: The dependent variables in the first column are a digital literacy score coming from correct responses to five digital literacy questions. The dependent variable in the second column comes from farmers' knowledge scores based on their responses to 14 questions about the apps they received training on. The dependent variable in the third column is a binary pass/fail indicator, assuming a value of 1 if a respondent passed the knowledge test (answered 6 or more questions correctly) and 0 otherwise. Standard errors, clustered at the village level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.2 Impacts on utilization and relevance of mobile applications

It is equally important to look beyond knowledge and assess the reported intensity of use of the different apps. The follow-up survey reveals that after the interventions, a larger share of the sample reported to be actively using the apps. Figure 4 below provides a closer look at the intensity of use per group, whereby the percentage of the T1 sample who reported to have used an agricultural app at least monthly increased from 2.2 percent at baseline to 22 percent post-interventions. Similarly, the T2 and T3 samples reported 19 percentage points and 15 percentage points increase, respectively, in their intensity of use.

Figure 4: Utilization and relevance of mobile applications



Meanwhile when analyzing farmer responses to the question of "How useful have you found mobile applications you use for farm purposes?" both at baseline and follow-up surveys, it is evident that farmers changed their perspective and assessment of the usefulness of digital tools. After the interventions—that is, after attending digital literacy trainings—when analyzing each treatment arm individually (Figure 4), the share of farmers in the first treatment arm (T1) who reported to have found digital apps useful or very useful, increased from 9.2 percent at baseline to 34.6 percent at follow-up; T2's corresponding share increased from 10.2 percent at baseline to 30 percent at follow-up, while T3's share rose from 8.9 percent to 25 percent over the same period. Interestingly, the increase in appreciation of digital tools among farmers exposed to the edutainment through the community play is smaller relative to farmers in the first treatment arm.

We now report parametric results estimated using equation (1). The first column in Table 5 report impacts on utilization of digital tools and farmer perception of digital apps usefulness. We measure utilization by computing how often a farmer uses an application for agriculture purposes, namely those who reported to have used an application at least once a month assume a value of 1 and the remaining farmers assume a value of 0. We measure the relevance of the mobile applications based on farmers' perception of the value and use of digital applications. Those who reported to have found digital apps useful or very useful for farm purposes assume a value of 1 and 0 otherwise. For both measures, we observe significant improvement across the three different treatment arms as reflected by the coefficients associated with the treatment indicator and interaction term. The estimates show that attending a digital literacy training session alone (T1), increased the likelihood that a farmer uses a digital tool at least once a month by up to 26 percentage points. Similarly, attending a digital literacy training session alone (T1) increases the likelihood that farmers perceive digital agriculture apps as useful by 22 percentage points. The p-values resulting from comparisons of the impact of the three different interventions show that the digital literacy alone appears to be relatively more effective than the digital literacy training and the complementing community play, reinforcing the previous results on the dilution effect of the community play.

Table 5: The impact of different digital promotional strategies on utilization and relevance

	Use digital app at least once a month	**Find digital app useful for farm activities**
Follow-up	0.074*	0.043*
	(0.043)	(0.022)
(T1) Training only #Follow-up	0.256***	0.218***
	(0.042)	(0.023)
(T2) Training + Video #Follow-up	0.255***	0.187***
	(0.059)	(0.036)
(T3) Training + Play #Follow-up	0.184***	0.123***
	(0.063)	(0.027)
Individual fixed effects	Yes	Yes
R-squared	0.084	0.155
Mean of the control group	0.119	0.096
Number of observations	4659	4659
Pairwise test (p-value)		
T1=T2	0.998	0.412
T2=T3	0.393	0.120
T1=T3	0.236	0.002

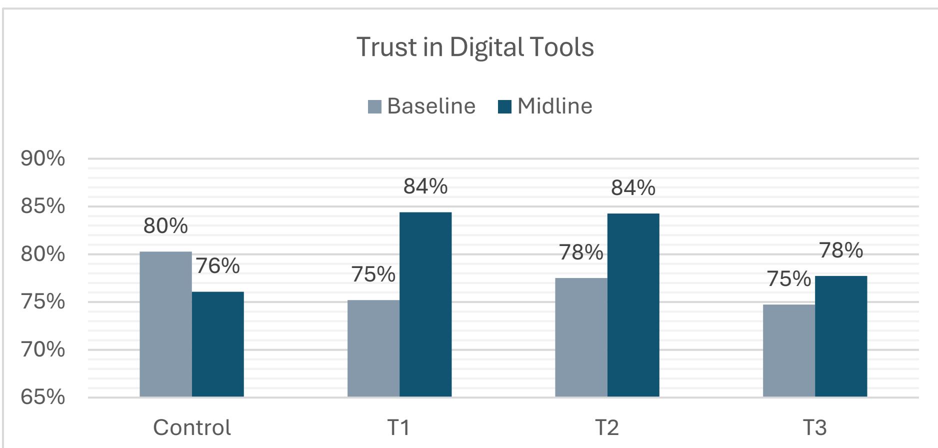
Note: The dependent variables in the first column are binary variables assuming a value of 1 if a respondent reports that they have used a digital app at least once and 0 otherwise. The dependent variables in the second column are binary variables assuming a value of 1 if a respondent reports that they find digital apps useful for farm activities and 0 otherwise. Standard errors, clustered at the village level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.3 Impacts on trust and interest in digital agriculture tools

Another important constraint to farmers' adoption of digital technologies—beyond lack of awareness, perceived utility, or the costs of accessing the internet or owning smartphones—is a persistent lack of trust. Fabregas et al. (2025), drawing on evidence from six African countries, highlight that trust-related concerns remain a major barrier to the uptake of digital tools. Farmers tend to prefer face-to-face channels due to fears of fraud, misinformation, and limited accountability in digital interactions, especially when platforms rely on one-way communication and are not mediated by familiar actors. Traditional marketing and advisory systems, such as local traders, retailers, and extension agents, are often perceived as more trustworthy than unfamiliar digital tools (Giulivi et al., 2023; Tabe-Ojong et al., 2024). Trust-related barriers are also shaped by concerns around data privacy, low confidence in navigating sophisticated digital apps, and the perceived risk of relying on automated tools whose logic is poorly understood by farmers (McFadden, 2022).

Against this backdrop, the results in Figure 5 indicate that digital literacy training played an important role in helping farmers overcome these trust barriers. Respondents were asked to report if they trust sharing and receiving farm information through the different agricultural digital apps. Delivered through farmer organizations, the training workshops significantly improved farmers' understanding of the relevance and functionality of agricultural apps. Figure 5 shows that, at follow-up, treatment group farmers witnessed significant increases in trust in digital tools when compared to baseline (ranging from a minimum of 3 percentage points to a maximum of 9 percentage points increase).

Figure 5: Do you trust sharing information through agricultural digital apps?



Similarly, the estimates in Table 6 show that the digital literacy training session alone (T1), increased the likelihood that a farmer trusts digital tools by up to 13 percentage points, and watching a video or attending a play along with a digital literacy training session (T2 and T3) can similarly increase the likelihood that farmers trust digital agriculture apps by up to 12 percentage points. These findings suggest that training sessions delivered by facilitators previously trained by the app developers helped bridge both technical and trust gaps, making digital tools more approachable and relevant to farmers. Similar patterns are observed in Fu and Akter's (2016) study in India, where farmers' aspiration to adopt new technologies increased following a mobile-app-based training program. In line with this, our estimates also show positive impacts on interest and approval of digital apps: farmers who attended digital literacy sessions are more likely to be interested in digital apps by up to 7 percentage points and are more likely to recommend digital apps for other farmers by up to 11 percentage points.

Table 6: The impact of digital promotional strategies on trust and interest in digital agriculture tools

	Trust in sharing/receiving information through Digital Apps	**Interest in Digital Apps for marketing services and price info**	**Recommend Digital Apps for other farmers**
Follow-up	-0.045^{*}	-0.041^{**}	-0.061^{**}
	(0.026)	(0.016)	(0.028)
(T1) Training only #Follow-up	0.133^{***}	0.069^{***}	0.106^{***}
	(0.038)	(0.021)	(0.029)
(T2) Training + Video #Follow-up	0.111^{***}	0.052^{***}	0.069^{***}
	(0.035)	(0.027)	(0.028)
(T3) Training + Play #Follow-up	0.071^{***}	0.059^{***}	0.089^{***}
	(0.032)	(0.018)	(0.029)
Individual fixed effects	Yes	Yes	Yes
R-squared	0.012	0.005	0.007
Mean of the control group	0.803	0.803	1.258
Number of observations	4659	4659	4659
Pairwise test (p-value)			
T1=T2	0.520	0.440	0.110
T2=T3	0.216	0.777	0.431
T1=T3	0.155	0.685	0.561

Note: The dependent variable in the first column is a binary variable assuming a value of 1 if a respondent reports that they trust sharing and receiving information through digital apps and 0 otherwise. The dependent variable in the second column is a binary variable assuming a value of 1 if a respondent reports they are interested in digital apps to access marketing service and price information, and 0 otherwise. The dependent variable in the third column is a binary variable assuming a value of 1 if respondents report that they would recommend digital apps to other farmers and 0 otherwise. Standard errors, clustered at the village level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

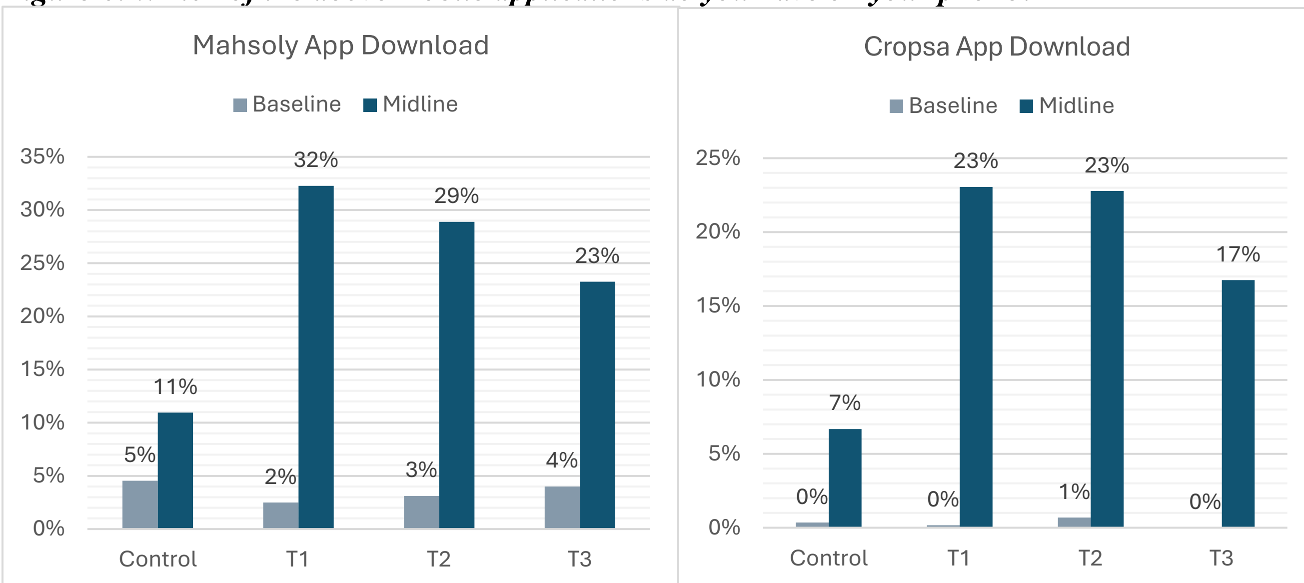
6.4 Impacts on uptake

To assess the impact of the interventions on uptake of digital agricultural tools, respondents were asked to report if they downloaded any of the different agricultural digital apps. By comparing the self-reported downloads of the Mahsoly and Cropsa apps in the baseline and follow-up surveys, Figure 6 shows that treatment group farmers reported significantly higher downloads, with increases ranging from a minimum of 17 percentage points to a maximum of 30 percentage points.[12] This is not surprising given that the training encouraged farmers to learn and ask questions about the different mobile app features, and trainers supported farmers who were interested in

[12] The control group farmers reported minor increase in downloads, implying that although some level of spillover effects cannot be ruled out, such effects are not large enough.

downloading the apps. The evidence that control group households experienced negligible change in their use and adoption of mobile applications suggests that spillover effects may not be pervasive.

Figure 6: Which of the above mobile applications do you have on your phone?



The estimation results computed using equation (1) show similar patterns. The two columns in Table 7 report impacts on uptake (downloads) of two selected agriculture digital applications that farmers received training on. We observe significant improvements in uptake across the three different treatment arms. For example, the digital literacy training alone increases the likelihood that farmers download digital apps by up to 20 percentage points. Our findings document even higher impacts than similar studies that implement comparable farmer training interventions, most of which report adoption and uptake rates that range only from 2 to 8 percent (Van Campenhout, 2021; Braganca et al., 2022; Priya and Singh, 2024).

It is, however, also visible that complementing training with a video does not yield major incremental differences in uptake in our intervention. This confirms evidence found in other contexts, where in Uganda, for example, the additional impact of a complementing video alongside training led to very limited impacts on the adoption and uptake of farm practices (Van Campenhout, 2021). Similarly, recent evidence from Ethiopia suggests that while replacing standard extension approaches with video-mediated delivery can moderately increase technology uptake, the effects, although statistically significant, remain modest in size (Abate et al., 2023b). These findings collectively highlight that while video interventions can enhance extension effectiveness, their incremental benefits, when layered onto training interventions, are often limited. At the bottom of Table 7 we report p-values associated with comparison of the effects of the different treatments. The reported p-values show that we cannot reject the null hypotheses that the effects of these treatments are statistically similar, except for the comparison between the digital literacy training alone and the digital literacy training plus community play.

Table 7: The impact of different digital promotional strategies on uptake

	Mahsoly Download	**Cropsa Download**
Follow-up	0.085***	0.065***
	(0.016)	(0.013)
(T1) Training only #Follow-up	0.198***	0.160***
	(0.025)	(0.018)
(T2) Training + Video #Follow-up	0.168***	0.161***
	(0.032)	(0.026)
(T3) Training + Play #Follow-up	0.110***	0.098***
	(0.026)	(0.021)
Individual fixed effects	Yes	Yes
R-squared	0.215	0.193
Mean of the control group (baseline)	0.030	0.002
Number of observations	4659	4659
Pairwise test (p-value)		
T1=T2	0.374	0.980
T2=T3	0.165	0.082
T1=T3	0.014	0.022

Note: The dependent variables in this table are binary variables assuming a value of 1 if a respondent reports that they have downloaded the specific mobile application and 0 otherwise. Standard errors, clustered at the village level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Indeed, in some comparisons, digital literacy training alone (T1) proved to be more effective, particularly in terms of increasing downloads, when compared to (T3). Two mechanisms may explain this unexpected finding. The first relates to class size: T3 sessions, scheduled after the community plays, averaged 22 farmers per session, compared to an average of 9 farmers per session in T1 and T2. This variation in class size likely influenced learning outcomes. Larger class sizes in T3 may have constrained trainers' ability to provide individualized support, reducing overall training effectiveness. As shown in Table 8, attending a community play increased attendance by up to 11 farmers relative to T1.[13] While edutainment can expand outreach and

[13] Digital literacy training sessions were designed for a maximum of 20 farmers each, with the objective to conduct 25 sessions per treatment arm. However, actual attendance varied: T1 and T2 averaged 9 farmers per session, requiring 51 and 52 sessions respectively, while T3 (community play) averaged 22 farmers per session, reaching the target sample in just 21 sessions, almost half the number of sessions required for T1 and T2.

engage populations in remote areas, an advantage widely recognized in the edutainment literature (Banerjee et al., 2019), there are limitations to be considered. Second, the lower adoption outcomes observed in T3 may also reflect social influence dynamics present in large group settings. Research on conformity shows that individuals align their beliefs and behaviors with those of their peers, especially in public group settings where they may perceive greater social pressure to conform (Gerard et al., 1968; Bond, 2005). In the context of our intervention, farmers attending the play and subsequent large group training may have been influenced less by the technical training content and more by prevailing group norms formed during the play. These norms, shaped in a socially engaging setting, likely emphasized collective opinions about the apps. If the emerging public opinion was ambivalent or skeptical, individuals would tend to conform to the majority view, undermining the training's efficacy, even if the content was understood accurately.

Table 8: The impact of different digital promotional strategies on class attendance

	Class size for each session	**Class size for each session**	**Class size for each session**
(T2) Training + Video	-1.123	-1.205	-1.202
	(0.893)	(0.854)	(0.855)
(T3) Training + Play	11.228***	11.281***	11.278***
	(0.975)	(0.939)	(0.944)
Constant	10.855***	8.089***	8.260***
	(0.782)	(0.627)	(0.784)
R-squared	0.495	0.826	0.826
Mean of the control group	14.519	14.519	14.519
Farmer organization fixed effects	No	Yes	Yes
Farmer characteristics	No	No	Yes
Number of observations	1719	1719	1719

Note: The dependent variable in this table is the class size associated with the session that farmers attended. In the first column, we do not add controls; in the second column, we control for farmer organization fixed effects; and in the third column, we additionally control for farmer characteristics, including gender, literacy, age group and farm size. Standard errors, clustered at the village level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Third, a growing body of literature suggests that edutainment may contribute to message dilution, where audiences focus more on the entertainment aspect rather than the educational message (Grady et al., 2021; Peterman, 2025). It is possible that the entertainment aspect of the play distracted from actual learning. This potential distraction effect is reflected in the literacy and uptake outcomes reported in Table 4 (columns 2 and 3), and aligns with findings from Van Campenhout (2021), who highlights that edutainment interventions may enhance engagement but do not necessarily drive behavioral change.

These findings raise broader questions about the conditions under which edutainment-based interventions can support behavioral change. According to social learning theory and behavioral change models, individuals adopt new behaviors through edutainment interventions only when they perceive those behaviors as aligning with their existing values and goals. However, fundamental values and goals are often resistant to change (Grady et al., 2021; Peterman, 2025). Such core beliefs may be difficult to shift through a single narrative exposure which may explain why community plays did not serve as a strong vehicle for social learning in this case. These findings offer valuable lessons for development practitioners. While community plays are powerful tools for attracting farmers and increasing reach, especially in remote areas, they may be less effective in driving individual-level learning and behavioral change in larger training settings where message dilution and conformity pressures are more pronounced.

7. Heterogeneity analyses and robustness checks

This section explores potential differential effects while also providing some robustness checks. We examine whether the impact of the different promotional strategies and training methods generate differential impacts across alternative observable characteristics of farmers, including gender, age, and farm size. We report these results in Appendix B. In Table B1, we extend this analysis by disaggregating the sample by farmers' gender, distinguishing between men and women. The findings reveal that women farmers were most positively impacted by the community play intervention. Specifically, the results in Table B1 indicate that, for the sample of farmers in T3, attending a community play and digital literacy training increased the likelihood of men downloading the Mahsoly and Cropsa apps by up to 9 and 8 percentage points, respectively. For women farmers, the impact nearly doubled, with increases of up to 20 and 18 percentage points, respectively. The p-values reported at the bottom of the table show statistically significant differences in these estimates. These differences may arise from lower baseline adoption rates among women, as existing research highlights that women face greater barriers to digital access, including lower mobile phone ownership, literacy challenges, and restrictive social norms (Spielman et al., 2021). Additionally, interactive storytelling and relatable characters in community plays have been shown to enhance engagement and behavioral shifts, particularly among marginalized populations (Grady et al., 2021). This aligns with our findings, where women farmers exhibited stronger responses to the edutainment-based intervention than men, suggesting that socially engaging learning models may be more effective in reducing digital adoption barriers for women.

Additionally, we hypothesize that younger farmers are more likely to regularly use and engage with digital tools. In Table B3–B4, we formally explore these differences by splitting the sample by age group, using the median age of respondents. The results align with our hypothesis, showing that for the sample of farmers in T3, younger farmers were more likely to use a digital tool at least once a month, with an increase of up to 15 percentage points compared to older farmers (8 percentage points). Similarly, younger farmers were also more likely to report finding digital apps useful, with an increase of 19 percentage points, compared to an 8-percentage point increase among older farmers. This is not surprising given the role of younger farmers in driving digital adoption because of their greater digital literacy, tech-savviness, and their openness to integrating digital platforms into their farming practices (Mehrabi et al., 2020; Aparo et al., 2022). Recent experimental evidence further confirms that younger and more educated farmers are more responsive to smartphone-based advisory services than older or less digitally familiar groups (Giulivi et al., 2022).

We also anticipate that poorer farmers, particularly smallholders, may derive the least benefit from the trainings, given their lower baseline familiarity with digital tools and structural constraints such as poor connectivity and lack of smartphone access (Appendix A). In Table B4, we formally estimate this disaggregating the sample among smallholders and medium holders, using the median farm size from our data as the threshold. The results indicate that farmers in T2 and T3 characterized as medium holders report higher uptake of mobile applications compared to smallholders. Similarly, Table B5 reveals that medium holders were more likely to report positive outcomes in terms of digital engagement. They expressed greater interest in digital apps, were more likely to recommend them to other farmers, and reported higher trust in sharing and receiving farm-related information through digital platforms.

These findings align with prior research indicating that smallholders are often marginalized in the digital transformation process. Previous studies have shown that younger and more educated farmers adopt mobile applications more readily than older and less-educated farmers, and that farmers with larger farms are more likely to integrate mobile technology into decision-making (Mehrabi et al., 2020; Aparo et al., 2022; Fabregas et al., 2025). Smallholders, by contrast, tend to be less familiar with digital platforms, which are increasingly essential for accessing agricultural information and market data. Consequently, they often struggle to navigate these platforms effectively or fail to realize their full potential (Baumüller et al., 2018). Overall, our heterogeneity analysis reinforces the notion that structural inequalities in digital access contribute to an uneven adoption of agricultural technologies. Identifying these differential adoption patterns is crucial for designing targeted interventions.

8. Concluding Remarks

The disconnect between widespread development of digital agricultural solutions and limited adoption at scale highlights the unrealized potential of digital innovations in Africa. While investment in digital agriculture continues to grow, its capacity to transform smallholder farming and improve market efficiencies remains largely unfulfilled. Despite the increasing enthusiasm for the potential of digital innovations to transform agrifood systems, adoption remains low and heterogenous in Africa. This can be attributed to lack of digital literacy as well as accessibility and usability constraints of existing digital tools and to the environment supporting these tools. Structural, economic, and socio-cultural barriers suggest that achieving widespread digital adoption requires more than just making digital tools available. Recent findings echo broader concerns and constraints that explain the persistent challenges to scaling digital innovations in agriculture, including infrastructure constraints and gaps in digital literacy (Abate et al., 2023a). These systemic barriers suggest that even well-designed interventions require broader ecosystem support to achieve transformative impacts at scale.

This paper evaluates alternative digital literacy training interventions aimed at promoting the diffusion of digital agricultural tools among smallholder farmers in Egypt. We specifically examine how different digital literacy approaches and edutainment nudges influence farmers' knowledge, utilization, trust, and uptake of these digital tools. All variants of digital literacy training significantly enhanced knowledge, utilization, and uptake. Notably, the training model that incentivized trainers based on farmers' knowledge test scores increased farmers’ knowledge about digital agricultural tools by up to 42 percentage points and raised uptake by up to 20 percentage points. Interestingly, while all training variants increased utilization intensity, relevance perceptions, and trust, the digital literacy training alone outperformed the combined approaches that incorporated edutainment nudges (video or community play) for some outcomes. Potential explanations for this include group size effects and social influence dynamics during community plays.

Our findings also indicate heterogeneity across farmer demographics; younger and more educated farmers were more likely to translate digital literacy training into active engagement with digital tools. While marginalized groups (smallholders and women farmers) also experienced positive impacts, structural barriers such as digital access constraints played a role in shaping adoption patterns. This underscores the importance of tailoring digital literacy interventions to varying learning capacities among diverse farmer groups. Indeed, evidence suggests that the effectiveness of digital extension tools is highly context-dependent, shaped not only by farmers' digital readiness and trust in the delivery channel but also by local infrastructure and demographic characteristics of target users (Fabregas et al., 2019; Giulivi et al., 2022).

Overall, our results suggest that investments in digital infrastructure coupled with targeted digital literacy training and complementary edutainment nudges can significantly enhance smallholder farmers' knowledge, utilization, trust, and uptake of digital agricultural tools. Our results paint a promising picture, with major improvements in the uptake and utility of digital tools as a direct result of the digital literacy training offered; in addition, we witness a clear shift in farmer beliefs and attitudes towards these tools for future adoption, whereby, the digital literacy trainings impacted farmer perception, trust, and interest in these tools, underscoring a clear opportunity for scale-up. Nonetheless, we caution against assuming that edutainment always strengthens adoption outcomes.

We conclude by acknowledging key limitations of our study. First, the results we document are short-term results, and whether such impacts sustain or not remains an important question worth addressing. Secondly, most of the outcomes we employ come from self-reported data, and revisiting impacts using actual utilization of digital tools for marketing and advisory services merits further investigation.

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Appendix A

Figure A1: Mobile phone and smartphone ownership among the sample

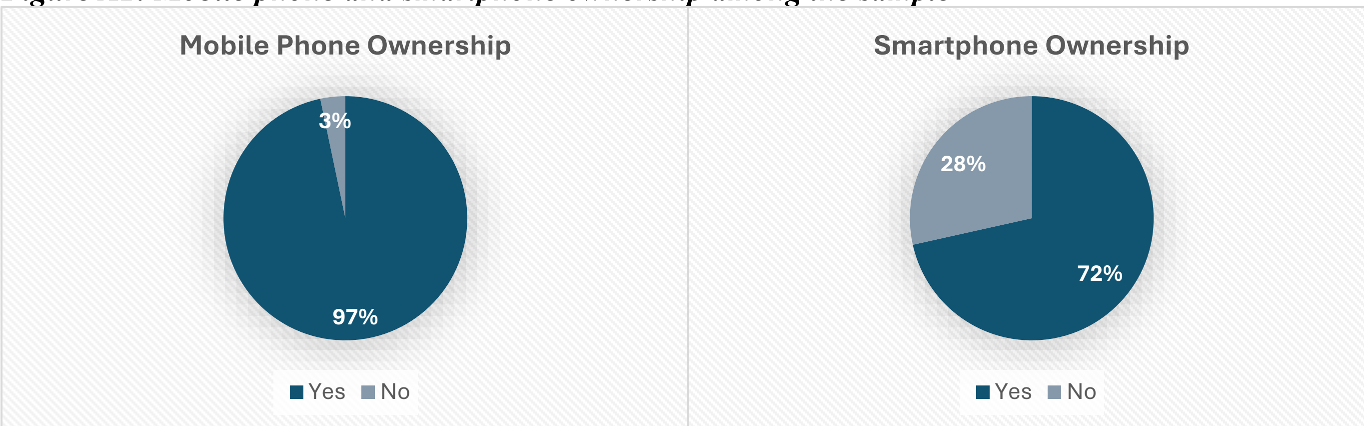
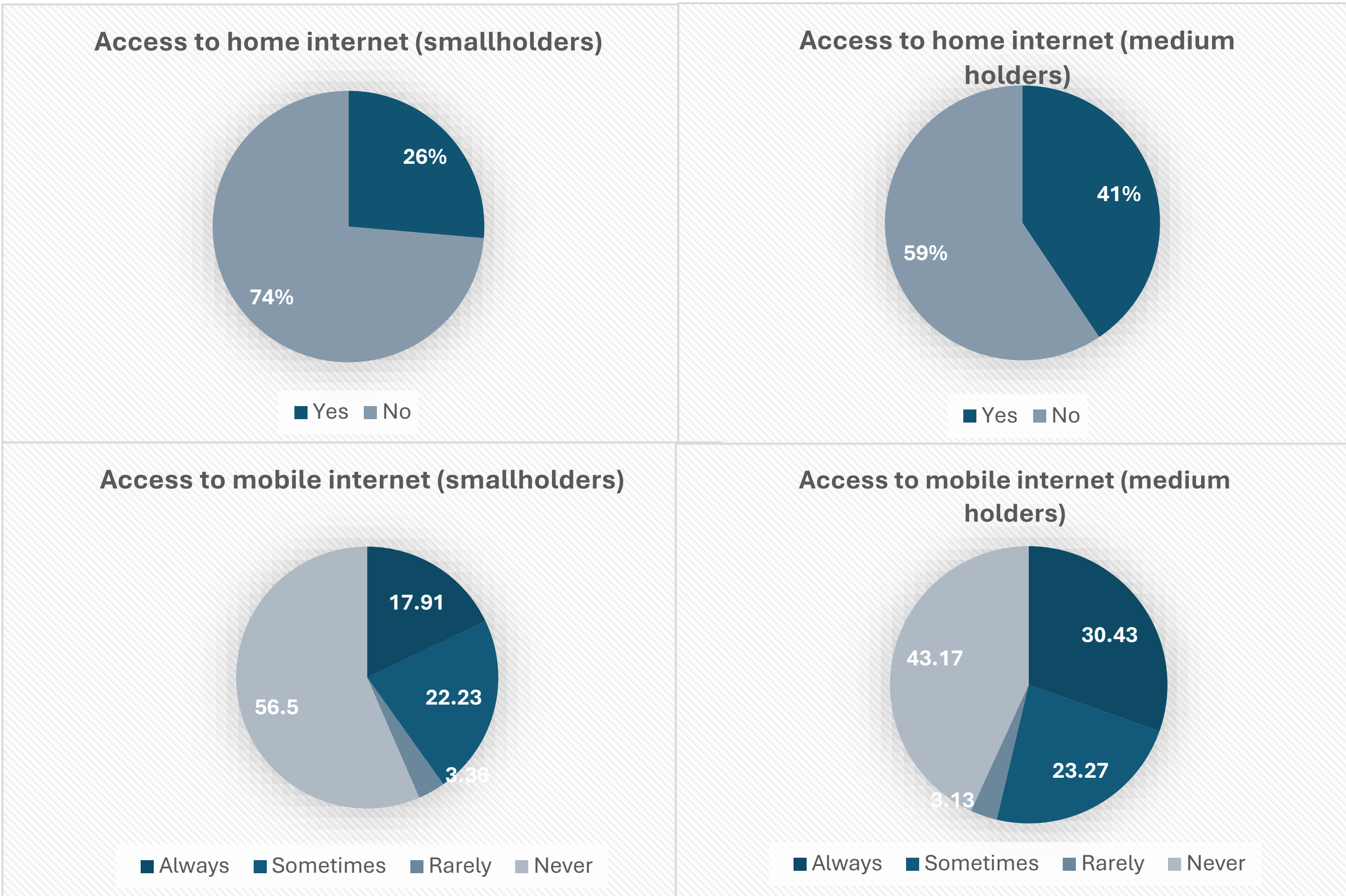


Figure A2: Smartphone ownership (smallholders vs medium holders)

Source: Authors' calculations based on (baseline) household data.

Figure A3: Home internet and mobile data access (smallholders vs medium holders)



Source: Authors' calculations based on (baseline) household data.

Appendix B

Table B1: The impact of digital promotional strategies on uptake by gender

	(1) **Mahsoly Download (Male)**	(2) **Mahsoly Download (Female)**	(3) **Cropsa Download (Male)**	(4) **Cropsa Download (Female)**
Follow-up	0.076^{***}	0.101^{**}	0.055^{***}	0.101^{**}
	(0.015)	(0.044)	(0.012)	(0.041)
(T1) Training only	0.196^{***}	0.275^{***}	0.159^{***}	0.210^{***}
#Follow-up	(0.028)	(0.062)	(0.020)	(0.050)
(T2) Training + Video	0.172^{***}	0.179^{***}	0.161^{***}	0.167^{***}
#Follow-up	(0.035)	(0.054)	(0.028)	(0.054)
(T3) Training + Play	0.093^{***}	0.200^{***}	0.088^{***}	0.186^{***}
#Follow-up	(0.025)	(0.059)	(0.022)	(0.050)
Constant	0.031^{***}	0.059^{***}	0.002	0.008
	(0.007)	(0.021)	(0.006)	(0.016)
R-squared	0.207	0.270	0.183	0.263
Mean control group	0.165	0.226	0.165	0.226
Number of observations	3918	741	3918	741
Pairwise test (p-value)				
Male=Female (T1)		0.339		0.480
Male=Female (T2)		0.970		0.979
Male=Female (T3)		0.066		0.049

Note: The dependent variables in this table are binary variables assuming a value of 1 if a respondent reports that they have downloaded the specific mobile application and 0 otherwise. Standard errors, clustered at the village level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: The impact of digital promotional strategies on utilization and relevance by gender

	(1) **Use digital app at least once a month (Male)**	(2) **Use digital app at least once a month (Female)**	(3) **Find digital app useful for farm activities (Male)**	(4) **Find digital app useful for farm activities (Female)**
Follow-up	0.034^{**}	0.038	0.027	0.063
	(0.017)	(0.037)	(0.019)	(0.045)
(T1) Training only	0.184^{***}	0.170^{**}	0.225^{***}	0.248^{***}
#Follow-up	(0.023)	(0.069)	(0.025)	(0.072)
(T2) Training + Video	0.170^{***}	0.169^{**}	0.204^{***}	0.168^{**}
#Follow-up	(0.033)	(0.077)	(0.038)	(0.070)
(T3) Training + Play	0.099^{***}	0.209^{***}	0.131^{***}	0.128^{***}
#Follow-up	(0.029)	(0.060)	(0.029)	(0.045)
Constant	0.068^{***}	0.130^{***}	0.088^{***}	0.153^{***}
	(0.006)	(0.015)	(0.007)	(0.017)
R-squared	0.135	0.130	0.158	0.155
Mean control group	0.062	0.133	0.090	0.129
Number of observations	3918	741	3918	741
Pairwise test (p-value)				
Male=Female (T1)		0.934		0.915
Male=Female (T2)		0.704		0.357
Male=Female (T3)		0.107		0.667

Notes: The dependent variables in column (1) and (2) are binary variables assuming a value of 1 if a respondent reports that they have used a digital app at least once a month and 0 otherwise. The dependent variables in column (3) and (4) are binary variables assuming a value of 1 if a respondent reports that they find digital apps useful for farm activities and 0 otherwise. Standard errors, clustered at the village level, are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table B3: The impact of digital promotional strategies on utilization and relevance by age group

	(1) **Use digital app at least once a month (Below median age)**	(2) **Use digital app at least once a month (Above median age)**	(3) **Find digital app useful for farm activities (Below median age)**	(4) **Find digital app useful for farm activities (Above median age)**
Follow-up	0.035*	0.042*	0.031	0.046*
	(0.019)	(0.023)	(0.023)	(0.025)
(T1) Training only	0.198***	0.184***	0.259***	0.209***
#Follow-up	(0.040)	(0.034)	(0.040)	(0.034)
(T2) Training + Video	0.199***	0.143***	0.202***	0.184***
#Follow-up	(0.057)	(0.046)	(0.052)	(0.049)
(T3) Training + Play	0.153***	0.086**	0.186***	0.082**
#Follow-up	(0.032)	(0.040)	(0.029)	(0.038)
Constant	0.081***	0.068***	0.107***	0.084***
	(0.010)	(0.007)	(0.011)	(0.007)
R-squared	0.152	0.137	0.172	0.160
Mean control group	0.086	0.062	0.112	0.078
Number of observations	2390	2269	2390	2269
Pairwise test (p-value)				
Young=Old (T1)		0.726		0.392
Young=Old (T2)		0.350		0.737
Young=Old (T3)		0.045		0.008

Note: The dependent variables in column (1) and (2) are binary variables assuming a value of 1 if a respondent reports that they have used a digital app at least once a month and 0 otherwise. The dependent variables in column (3) and (4) are binary variables assuming a value of 1 if a respondent reports that they find digital apps useful for farm activities and 0 otherwise. Standard errors, clustered at the village level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: The impact of digital promotional strategies on uptake by farm size

	(1) **Mahsoly Download (Smallholder)**	(2) **Mahsoly Download (Medium holder)**	(3) **Cropsa Download (Smallholder)**	(4) **Cropsa Download (Medium holder)**
Follow-up	0.073^{***}	0.097^{***}	0.069^{***}	0.061^{***}
	(0.022)	(0.020)	(0.018)	(0.013)
(T1) Training only	0.206^{***}	0.191^{***}	0.143^{***}	0.176^{***}
#Follow-up	(0.036)	(0.040)	(0.029)	(0.024)
(T2) Training + Video	0.159^{***}	0.176^{***}	0.115^{***}	0.208^{***}
#Follow-up	(0.035)	(0.037)	(0.031)	(0.037)
(T3) Training + Play	0.088^{**}	0.131^{***}	0.072^{**}	0.123^{***}
#Follow-up	(0.035)	(0.028)	(0.028)	(0.024)
Constant	0.030^{***}	0.040^{***}	0.003	0.004
	(0.009)	(0.007)	(0.008)	(0.007)
R-squared	0.195	0.236	0.166	0.220
Mean control group	0.165	0.183	0.165	0.183
Number of observations	2263	2392	2263	2392
Pairwise test (p-value)				
Small=Medium (T1)		0.801		0.388
Small=Medium (T2)		0.661		0.034
Small=Medium (T3)		0.252		0.097

Note: The dependent variables in this table are binary variables assuming a value of 1 if a respondent reports that they have downloaded the specific mobile application and 0 otherwise. Standard errors, clustered at the village level, are given in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: The impact of digital promotional strategies on trust and interest by farm size

	(1) **Trust in Digital Apps (Smallholders)**	(2) **Trust in Digital Apps (Medium holders)**	(3) **Interest in Digital Apps (Smallholder)**	(4) **Interest in Digital Apps (Medium holders)**	(5) **Recommend Digital Apps (Smallholder)**	(6) **Recommend Digital Apps (Medium holders)**
Follow-up	0.015	-0.100***	-0.004	-0.075***	-0.015	-0.104***
	(0.033)	(0.030)	(0.028)	(0.017)	(0.041)	(0.028)
(T1) Training only	0.074	0.188***	0.045	0.092***	0.056	0.151***
#Follow-up	(0.047)	(0.045)	(0.035)	(0.025)	(0.042)	(0.035)
(T2) Training + Video	0.058	0.160***	0.004	0.098***	0.030	0.104**
#Follow-up	(0.047)	(0.050)	(0.038)	(0.029)	(0.038)	(0.040)
(T3) Training + Play	0.005	0.132***	0.058**	0.059**	0.036	0.139***
#Follow-up	(0.038)	(0.048)	(0.029)	(0.025)	(0.045)	(0.035)
Constant	0.755***	0.783***	0.897***	0.933***	0.848***	0.866***
	(0.009)	(0.009)	(0.006)	(0.005)	(0.011)	(0.009)
R-squared	0.011	0.017	0.008	0.013	0.003	0.017
Mean control group	0.766	0.837	0.916	0.943	0.088	0.103
Number of observations	2263	2392	2263	2392	2263	2392
Pairwise test (p-value)						
Small=Medium (T1)		0.033		0.281		0.073
Small=Medium (T2)		0.143		0.031		0.176
Small=Medium (T3)		0.038		0.962		0.072

Note: The dependent variables in column (1) and (2) are a binary variable assuming a value of 1 if a respondent reports that they trust sharing and receiving information through digital apps and 0 otherwise. The dependent variables in column (3) and (4) are a binary variable assuming a value of 1 if a respondent reports they are interested in digital apps to access marketing and price information and 0 otherwise. The dependent variables in column (5) and (6) are a binary variable, assuming a value of 1 if respondents report that they would recommend digital apps to other farmers and 0 otherwise. Standard errors, clustered at the village level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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