Getting the message out: Information and communication technologies and agricultural extension

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Abstract

There has been much optimism about the potential of information and communication technologies (ICTs) to provide agricultural extension services to remote households. Yet, little is known about how different communication methods fare, and, moreover, whether different segments of the population adopt information communicated via different means equally. We conduct a randomized control trial comparing the effectiveness of three ICTs — radio, voice response messages, and a smartphone app — with traditional extension training in communicating fertilizer management practices across four districts in rural Nepal. We find that farmers in the smartphone app and the extension training programs are on average 8.4% and 13% more likely to adopt top dressing fertilizer practices compared to control farmers at the 1% and 5% statistical levels of significance, respectively. Farmers in the smartphone app treatment achieve the highest agronomic literacy test scores, 7.8% higher than the control with 1% statistical significance. Our results suggest that smartphone apps are more cost effective at inducing farmer knowledge and technology adoption than extension trainings. Heterogeneous treatment effects, however, reveal that a targeted ICT approach may be more effective in disseminating extension advice.

Keywords: Extension, information communication technologies, Nepal, trust

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1. Introduction

Agriculture is the principal occupation for 65% of poor working adults in developing countries (Castaneda et al., 2016). In this context, increasing agricultural productivity is key to promoting economic growth and food security. The agricultural productivity gap between developed and developing countries continues to widen, which can, in part, be attributed to low adoption rates of improved technologies among farmers in developing countries (Nakasone et al., 2014). Extension services have been traditionally used to bridge the gap between research and innovation for farmers by providing information on, for example, recommended input applications (e.g., fertilizers and seeds), best cultivation and pest management practices, etc. (Aker, 2011; Norton and Alwang, 2020). While there is evidence of positive returns to extension services, e.g., in the context of contract farming (Bellemare, 2010), extension services often come with high implementation costs and have been criticized for being difficult to monitor, e.g., number of trainings given and list of attendees (Anderson and Feder, 2007). Some implementation costs and communication inefficiencies have been reduced with farmer field days and/or demonstration plots, whereby farmers meet to learn about a new technology by seeing it implemented by peer farmers (Emerick and Dar 2021; Dar et al., 2020; Pan and Zhang 2018; Larochelle et al. 2017). Furthermore, the increasing penetration of mobile communication technologies (e.g., smartphone and other mobile phone devices), has made Information and Communication Technology (ICT) tools a promising avenue to facilitate information dissemination (Fabregas et al., 2019).

In this study, we test the comparative effectiveness of mobile phones as well as other ICT tools in delivering extension services to farmers, and assess their substitutability to in-person extension services. This is particularly salient given the limited mobility of people to deliver information following the global COVID-19 pandemic, and the increased reliance on ICT tools due to lockdown measures enacted in many countries. More specifically, we study how three ICT tools -- radio messages, interactive voice response messages (IVR) and a remotely accessible smartphone app -- used to deliver agricultural advice impact farmers' knowledge and adoption of new fertilizer management practices relative to traditional 'classroom and field' based extension training. In particular, we attempt to answer the following questions: (i) can the dissemination of information regarding new agricultural technologies via ICT tools be equally or more effective than through traditional extension trainings in inducing knowledge and adoption of the recommended practices?; (ii) among the ICT tools, will farmers learn and adopt the most when the information is delivered via traditional technologies (i.e., radio) compared to more novel, mobile-based, sources (i.e., IVR and smartphone app)? We additionally test how farmers' trust in the different ICT tools affects their adoption rates and look into the heterogeneous effects of the treatments by gender and wealth levels. Determining how certain segments of the population respond to different tools is important since farmers may not have access or affinity to using the same mobile technologies, such that focusing agricultural extension via ICTs could contribute to a digital divide, e.g., poorer farmers, more remote farmers or female-headed households may not own or may have limited access and/or network coverage and/or preferences for using mobile devices.

To our knowledge, this is the first paper to compare different ICT tools, including two variations of mobile-based services (i.e., radio vs. voice response messages (IVR) and a smartphone app), in delivering agricultural extension services to farmers. We are also the first paper to assess the substitutability of these different ICTs to in-person extension services by comparing the ICT treatments to a traditional in-person extension training. The benefits of using ICT tools in agricultural markets have been explored by Jensen (2007)'s pioneering work where he studied the benefits of mobile phone towers in South India on price dispersion in the sardines fish market. Since, there has been a growing body of literature looking at the use of ICTs to deliver learning and adoption benefits in the context of agricultural extension. Most of these studies have focused solely on testing the effectiveness of a mobile-based service ranging from inexpensive tools (e.g., SMS, voice messages, low-cost participatory agricultural extension videos), to highly sophisticated platforms (e.g., apps using virtual reality, multi-media platforms, etc.). For example, Casaburi et al. (2014) and Cole and Fernando (2016) and Kadiyala et al., (2016) find that agricultural recommendations shared through either SMS reminders, weekly voice messages or extension videos developed by Digital Green, respectively, are effective at increasing yields between 8 % -28% compared to the control group, as well as encouraging overall experimentation with the advice provided. A study by Tjernstrom et al. (2021) is the only one we are familiar with that examines the use of smartphones for extension services. They look at learning outcomes of Kenyan farmers using an app that allows users to experiment with different fertilizer applications on maize crops on a virtual plot, though they do not look at the effect of the experiment on actual on-farm adoption. None of these studies, however, compare the effectiveness of different ICT tools. Van Campenhout (2021), however, does look at how effective ICTs are in relaxing information inefficiencies relative to other barriers, e.g., risk or credit constraints. He finds that ICTs are not as effective at sharing information than reducing other barriers. In this study we contribute to this comparative literature. Furthermore, we begin to examine the mechanisms that might affect learning and adoption outcomes by examining the different technology features (e.g., auditory vs visual, frequency of information, accessibility, etc.), focusing on the role of trust, in particular.

To examine the issues raised, we run a randomized control trial in Nepal with four treatment arms (i.e., radio messages, IVR, smartphone app and traditional extension training) to compare the relative effectiveness of these different tools to disseminate fertilizer recommendations. More specifically, we recommend farmers apply fertilizers at two specific times, a primary, 'basal' application of diammonium phosphate (DAP) at planting, and two secondary 'top-dressing' applications of urea, when the plant has six leaves (vegetative stage 6, v6) and then ten leaves (vegetative stage 10, v10). We find that farmers in the smartphone app treatment are 6% more likely to apply urea at v6 and v10 compared to farmers in the control group (5% statistical significance). Furthermore, farmers within the smartphone app treatment achieve 9% higher agronomic test scores for questions directly relating to the fertilizer application, and 6% higher test scores for questions measuring general agronomic knowledge (1% and 5% levels of statistical significance, respectively). Traditional extension training programs are also effective disseminating knowledge, increasing the adoption of urea at v6 and v10 by an average of 10% at the 5% confidence level compared to control farmers. However, no significant effects were found from any treatment on the basal fertilizer use at planting. We find suggestive evidence that this may result from an asynchrony between the timing of the messages and the actual time of planting rather than the method of delivery, and/or the high cost of the basal fertilizer, DAP. We also find that similar to Fu and Aker (2016), wealthier farmers in the traditional extension training and smartphone app treatments were less likely to adopt the top-dressing fertilizer application recommendations compared to middle-and-low-income farmers. Additionally, female farmers are more likely to follow the top-dress fertilizer application recommendations in the radio and traditional extension training programs, compared to men.

The remainder of this text is organized as follows. Section 2 presents a conceptual framework. Section 3 explains the context in Nepal and the experimental design. Section 4 describes the methods used, which are reported in section 5 and discussed in section 6. Section 7 concludes.

2. Conceptual framework

To understand why certain technologies may induce greater learning and adoption, we examine some of the differentiating features of these technologies. The relationship between the source of information, i.e., from a specific ICT or an extension agent, relates to both the learning and technology adoption literatures. We therefore follow the framework of Foster and Rosenzweig (1995) who model farmer learning in a Bayesian model framework. We designate farmer *i* as having a prior belief about output, $\widehat{q_i}$, which is normally distributed around a true value, q_i, and variance of σ_q^2.

$$\widehat{q_i} \sim \mathcal{N}(q_i, \sigma_q^2)$$

Farmer *i* receives an information signal f_i via an ICT which gives information about q_i with a noise signal of ν_i. ν_i is normally distributed with a mean 0 and is a function of a vector of features related to a specific ICT, s $\in${radio, IVR, app, extension}.

$$f_i = q_i + \nu_i$$

$$\nu_i \sim \mathcal{N}(0, \sigma_\nu^2(s))$$

The more amenable a farmer is to a certain ICT, the lower the variance. In other words, if a farmer receives information from two sources, *a* and *b*, where the farmer prefers a to b, $a \succ b$, then

$$\sigma_v^2(s_a) < \sigma_v^2(s_b)$$

If expected profitability of adopting the information is positive (negative), E[Π] > (<) 0, then a farmer will be more (less) likely to adopt if she receives information via source a.

Given the importance of trust in economic transactions, we examine how trust affects adoption of information transmitted via different ICTs. If σ_v^2 is also a function of trust, *r*, in addition to attributes of ICT *s*, then for a fixed s,

$$\sigma_v^2(\bar{s}, r_1) > \sigma_v^2(\bar{s}, r_2)$$

If $r_2 > r_1$, where a higher r value represents a more trusting farmer. In other words, for the same technology, we expect a more trusting farmer to gain more precise information on q_i, thereby increasing their likelihood of adopting the information. In Appendix I, we discuss other ICT features that might affect adoption. These other characteristics can be examined under the same framework proposed here. However, given our experimental design we can only specifically test for the effects of trust on adoption, presented after our main empirical results below.

3. Experimental Design

3.1 Context

Nepal is a landlocked country in South Asia with an economy heavily reliant on the agricultural sector, which accounts for 28% of the gross domestic product (GDP) and employs 60% of the labor force (Ministry of Finance, 2019). Nepali agriculture is dominated by smallholder farmers following traditional farming practices (Adhikari et al., 2018). Low agricultural productivity has been endemic as more than half (54%) of the Nepali population is affected by chronic food insecurity (IPC, 2014). One of the major reasons cited for poor agricultural productivity is the low use of fertilizers (United States Agency for International Development (USAID), 2012). Ensuring timely access and appropriate application of mineral fertilizer is therefore key to agricultural development, food security and poverty reduction in the region (Vanlauwe et al., 2010).

The agricultural sector in Nepal is formally and informally organized into cooperatives. Cooperatives play a crucial role in the dissemination of subsidized fertilizers, as they are the only place where farmers can purchase official government subsidized fertilizers. While formal agricultural extension has been provided by the public sector, limited government resources and complex terrain contribute to low access of formal extension services across the country. A recent survey conducted by CIMMYT in Nepal revealed that only 5% of farmers have access to formal extension services. To partially fill in this void, some cooperatives provide informal extension services. At the same time, this same survey revealed that despite the relative poverty and remoteness in Nepal, 85% of surveyed farmers reported having access to mobile phones and other communication technologies, either directly or indirectly through their local cooperative, lending credence to a potential role of ICTs to enhance access to agricultural extension services.

Furthermore, the number of smartphone users has been increasing steadily in Nepal, growing from 15% in 2013 to 59% in 2018 (the year of this study) to 65% in 2020 (NepaliTelecom, 2021).

3.2. Study design

Between May and October 2018, we conducted a randomized control trial (RCT) in four districts in Nepal: Kavrepalanchok, Surkhet, Dang and Palpa. These four districts, located in the hills, were selected because they are prominent regions where maize is considered an important food commodity and input for poultry feed. Additionally, in the hills traditional extension services are more limited due to low extension reach and high costs which may be regions where ICT-based extension services may have comparative advantages relative to traditional extension methods. Finally, each district had access to mobile coverage[1].

In each of the four districts, we conducted a survey of all 105 cooperatives growing maize. From this survey, 15 cooperatives were randomly sampled per district, for a total of 60 cooperatives invited to participate in the study. With limited data on adoption of different ICTs, we used agronomic data on the expected maize yield gains from applying fertilizer at the recommended time (V6 and V10) to estimate our power calculations. We were powered to detect a 1061 increase in maize yields[2] allowing for clustered randomization with three treatment arms[3]. Randomization of the treatment arms was done at the cooperative level: 10 cooperatives were randomly assigned to each of our four treatments, described below in more detail. Twenty cooperatives were randomly selected into the control group in which farmers received no

[1] See online Appendix, Figure A: selected districts are highlighted in green.
[2] CIMMYT agronomic field trials cited up to an average of 2 tons/ha increase in yields from correctly timing the application of fertilizer
[3] We used Stata's clustersampsi command: clustersampsi, detectabledifference mu1(3880) sd1(1532) m(30) k(15) rho(0.25).

information on fertilizer application timing (Figure 1). Randomization was done at the cooperative level for three reasons. First, as aforementioned, cooperatives are one of the primary ways in which farmers receive information in Nepal, making it a convenient way to disseminate information and extension services. Second, cooperatives are one of the main social networks utilized by farmers, especially in which agronomic information is shared. Lastly, Nepal is a country of high geographical diversity. Many farms and villages are located in remote hills and valleys with limited accessibility. Randomizing at the cooperative level was logistically more feasible given our time and resource constraints.

Fifteen farmer participants were randomly sampled from each cooperative, resulting in a full sample of 900 participants who were interviewed at baseline (pre-treatment) in May 2018 and end-line (post-treatment) at the end of September 2018, post maize harvest. Randomly selected respondents were interviewed at baseline if they had planted maize in the 2018 season and had access to both a radio and a smartphone. Access to a smartphone was defined as directly owning a device or indirectly accessing it from a neighbor or other household member at least 3 times a week. This rule was applied to achieve a more representative sample of participants. Only 14 respondents from the baseline dropped out of the study, representing an attrition rate of 1.55%, leaving us with a total sample of 886 respondents[4].

Figure 1 here

[4] We regress treatments on whether households attrit and find that attrition does not differ between treatments and the control group. Results are available from the authors upon request.

3.3 Treatments

The treatments provided agricultural recommendations regarding the optimal timing for fertilizer on farmers' maize crops. More specifically, the recommendation included applying DAP as a primary or basal fertilizer at planting, and a secondary or topdressing application of urea fertilizer in two doses, at vegetative stage 6 (v6) (i.e., when the maize plant has six fully grown leaves) and vegetative stage 10 (v10) (i.e., when the maize plant has ten fully grown leaves). Farmers were given detailed information on how to identify if the plants were ready for the application of each dose of urea. To identify whether the plots were ready for the first urea application, farmers were advised to pick five plants at random on their main maize plot and count their leaves. If at least three out of those five plants had six fully formed leaves, this was to be interpreted as the optimal time to apply the first half of the urea application (v6 stage). The same process was suggested for the second application of urea — farmers were recommended to apply the second dose of urea when three out of five plants had ten fully formed leaves (v10 stage). The advice for each treatment was the same, except it was shared either via a remotely accessible smartphone app; a traditional, in-person extension training; radio messages; or IVR messages sent through phone calls.

Traditional fertilizer management for maize for many smallholder systems around the world is to apply a planting fertilizer (commonly DAP) at planting by broadcasting throughout the field. Top-dress fertilizer (commonly urea) is applied when the maize plants in the field have roughly reached the height of the farmer's waist and again when the maize plants have reached the height of the farmer's shoulder. However, in many cases, only one top-dress application of fertilizer is applied. The improved timing of fertilizer application at these two specific stages of maize plant growth (v6 and v10), was shown to exhibit maximal nutrient uptake by the plants, leading to less fertilizer waste and increased yields by up to an additional 2 tons/hectare according to International Maize and Wheat Improvement Program's (CIMMYT's) field trials in Nepal.[5]

Traditional Extension Training

The traditional extension training was delivered by CIMMYT field staff in each respective randomly selected cooperative[6]. The training consisted of an audio-visual presentation of the new farming practices on fertilizer application timing using printed paper slides (Appendix B), followed by a hands-on field plot demonstration. The extension training was conducted in farmers' cooperatives or designated locations within the villages. The randomly selected farmers received a telephone call with an invitation to attend the extension training at a specified time and location. Farmers assigned to the extension training also received a printed paper poster guide of the fertilizer application practices, allowing participants to refer back to the training materials at any time.

Radio Program

The radio treatment was created in partnership with V-Chitra, a Nepali media agency specializing in marketing provision and advertising services. All radio messages lasted approximately one minute and were aired as a dialogue between a man and a woman, using local names for the characters. The messages discussed the DAP and urea recommendations provided by the treatments described above (see Appendix C for full script). Two follow-up radio messages

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[5]Yield response to fertilizer generally depends on both the amount applied and the application method/timing. Urea topdress timing, however, was shown to not depend entirely on the quantity of fertilizer used, the variety of maize grown, or by soil type (Campolo et al. 2021).

[6]It is likely that the extension services provided by CIMMYT do not perfectly represent the national extension services. While CIMMYT works closely with Nepal's national agricultural extension network, due in part to the additional resources CIMMYT has access to, the results of the extension services provided in this project are likely to over-report the effect that traditional extension services might offer.

contained detailed explanations on how to count leaves. The first radio message was aired between the 28th of May until the 4th of June, 2018. The two additional radio messages were timed to coincide with the approximate dates when farmers' maize plots would be ready for the first application of urea at v6 stage (between the 4th of June until the 18th of June, 2018), and for the second application of urea at v10 stage (between the 2nd of July to the 16th of July, 2018) given farmers' planting dates. The messages were aired as advertisement breaks after popular radio programs at five different times during the day (7:15-7:30am, 8:15-8:30am and in the evening at 6:15-6:30 pm, 8:15-8.30pm and 9:15-9:30pm), which were the most common times during which farmers listened to the radio, according to the baseline data.

Anyone who had access to a radio could have heard the radio program. In order to minimize spill-over between the radio treatment with other treatments, the recommendations were aired through the second most popular radio station in each district. To encourage participants in the radio treatment to tune into the radio at the right times, participants were sent voice response message reminders to tune into the radio at specific times. Farmers received reminder calls to tune into the radio every other day (between the 1st and 17th of June and again between the 27th of June to the 16th of July, 2018, approximate dates that corresponded to the v6 and v10 stages for maize in these regions). This way, farmers in the radio treatment would be more likely to tune into the treatment radio stations at the time the messages aired.

IVR (Interactive Voice Response) messages

The IVR treatment was tested as an alternative method of communication with the potential of reaching illiterate farmers, contrary to SMS-based messages and apps. The Agri-tech organization, Viamo, led the development and implementation of the IVR treatment arm. The literacy rates in

Nepal are estimated to be 67.9% of people aged 15 and above in 2018 (World Bank, 2019), though literacy rates in more remote areas are expected to be lower. Farmers randomly assigned to this treatment received a phone call containing an automatic response message that was programmed to play as soon as farmers picked up the phone. Three main calls were sent through the IVR treatment: a general call and two follow up calls to remind farmers to apply urea fertilizers at v6 and v10 stages of plant growth (see Appendix D for full script). The first call contained the same dialogue as the radio messages, but with an introduction letting farmers know that it was an automatic voice response message delivered by CIMMYT. The second and third calls again contained the same information as the radio messages, but had an additional interactive feature asking participants questions regarding the information provided in the first call in which they could use the keypad to answer[7]. This was a means to engage farmers during the calls and check their understanding of the information. The information was synchronized by planting dates to ensure the information arrived at an appropriate time. Viamo sent the first call (1-minute-long), followed by the second call (1:50 minutes long), leaving a one-day break in between the first two calls. These calls went out from the 1st of June to the 17th of June, 2018. The last call was sent from the 29th of June until the end of July, 2018 — depending on farmers' planting dates — leaving at least a two-day break in between the second and third calls (1:50 minutes long).

App

The smartphone app, called MKrishi, developed by a Nepali ICT firm, Geokrishi, was made simple and easy to use. It contained static slides with illustrations on the techniques of when to apply

[7] The question asked for call 2 was: "Do you remember when to apply the first half of urea to your maize plants? Press 1 if you think it's at planting. Press 3 if you think it's when six leaves have fully formed". The question asked for call 3 was: "Do you remember which fertilizer you should apply when your maize has ten fully formed leaves? Press 1 if you think it's urea. Press 3 if you think it's DAP". For a full script refer to Appendix D.

fertilizers and how to count leaves to apply urea fertilizers at the two specific stages of maize plant growth. It included text as well as an audio option to listen to voice recorded readings for illiterate users. The slides used in the app were the same as the ones presented during the extension training given by CIMMYT's field staff (see Appendix B), with the main difference between the two treatments being the convenience and ease of access to information from the smartphone app as well as its interactive and appealing format of presenting the information (i.e., digital images with audio in a mobile device). As the app was not publicly available, CIMMYT staff contacted each randomly selected participant assigned to receive the app treatment and invited them to meet at a specific location to redeem the app during a group meeting with the rest of the randomly selected farmers assigned to the app treatment. CIMMYT staff did not deliver a training on how to use the app, nor did they provide additional information regarding the fertilizer recommendations. After receiving the app, farmers were given time to review the app on their phones to check that they were able to access all of its features.

4. Methods

To measure the effect of different information communication technologies on farmer knowledge and adoption, we estimate the following analysis of covariance (ANCOVA) model (1),

$$Y_{ic}^{endline} = \alpha + Y_{ic}^{baseline} + \beta_k T_{ic} + \gamma X + \varepsilon_{ic} \qquad (1)$$

where $Y_{ic}^{endline}$ is the outcome variable of interest at endline and $Y_{ic}^{baseline}$ is the outcome variable of interest at baseline, defined further below, for farmer *i* in cooperative *c*. Equation (1) is estimated using ordinary least squares, including the adoption outcomes where the dependent variable is binary. The treatment variable is denoted by T_{ic} and takes a value of 1 if individual i in cooperative c was randomly assigned to that treatment, or 0 otherwise. The main parameter of interest is the β coefficient, which shows the intention-to-treat effect on the outcome variable of interest. Equation (1) is estimated both with and without controls. The vector of controls is denoted by X and includes the imbalanced characteristics identified at baseline, discussed further below. Finally, ε_{ic} is the error term, which we cluster at the cooperative level.

In Equation (1), we estimate the effect of each treatment individually relative to the control group, denoted by β_k. In order to compare how the different treatments fare relative to each other, we also estimate equation (2) below where each treatment is controlled for simultaneously,

$$Y_{ic}^{endline} = \alpha + Y_{ic}^{baseline} + \sum_{k=1}^{3} \beta_k T_{ic} + \gamma X + \varepsilon_{ic} \qquad (2)$$

Where the variables represent the same as those described above. The parameters of interest here are β_1, β_2, β_3.

4.1. Outcome variables

The study measures the effectiveness of information communicated through different ICT channels on two main outcome variables: (i) the adoption of new agricultural technologies, and (ii) knowledge about the new farming practices. Both variables were collected through self-reported data using questions which evaluated farmers' retention of the information provided and enquired about adoption of the recommendations.

At baseline, farmers were asked whether they applied urea and DAP fertilizers to their maize crops, and the techniques they used to determine if the soil was ready for fertilizer application (timing of fertilizer application) in the 2017 monsoon season. Farmers were then asked the same questions for the 2018 season at endline (post intervention and immediately after harvest). One of the survey options included whether they split the application of urea in two doses by counting leaves at v6 and v10 stages of maize plant growth. Another question asked whether they applied DAP fertilizer only at planting.

Larochelle et al. (2017) is the first paper to explicitly test learning outcomes by conducting two agronomic literacy tests after sending text message reminders following a three-day long farmer field day (FFD) on integrated pest management (IPM) practices to potato farmers in Ecuador. We followed a similar approach whereby we measure two agronomic literacy test scores from questions conducted during both baseline and endline surveys. The agronomic questions contained 11 multiple-choice questions, which measured general agronomic knowledge regarding fertilizers, seed varieties and pest/disease. Among these questions, 6 of them were specifically related to the information provided by our treatments, regarding the optimal timing of urea and DAP application, as well as the distance to apply fertilizers from the maize plants. Two percentage scores were therefore constructed from these agronomic tests. The first is a *general agronomic knowledge score*, assigning 2 points for each right answer, and 1 point for each partially right answer. A second percentage score called the *relevant agronomic knowledge score*, was created following the same procedure, except it only included the 6 relevant questions related to the treatments (the questions asked to generate both scores can be found in Appendix E). Knowledge scores represent the percentage of questions answered correctly. The relevant agronomic knowledge score is an important focus of this study since it captures the knowledge coming directly from the information provided by the treatments.

4.2. Intention-to-Treat Effects (ITT) and Compliance

Equation (1) above measures the intention-to-treat (ITT) effect and is used to estimate the coefficients for all the respondents who were randomly assigned to the treatments, regardless of whether they used the treatments or not. Compliance rates for this study are presented in Table 1. The data in column 2 of Table 1 describe the number of farmers who used the treatments, as opposed to those who were randomly assigned to receive them (column 1). These data were gathered through attendance lists that recorded how many farmers showed up to the meetings to receive the extension training or the smartphone app. For example, out of the 150 farmers who were invited to receive the extension training, only 105 of them actually attended the extension training event. The radio and IVR treatment data were gathered by the company Viamo, who recorded data on whether farmers picked up the calls or not, independently of whether they listened to the full length of the call. The data for the IVR presented in the second column of Table 1 are for the first IVR call that farmers received, which included all of the fertilizer recommendations summarized (applying urea in two doses at v6 and v10 and DAP only at planting). Farmers randomly assigned to the radio treatment received IVR reminders to tune into their selected district radio stations at specific times of the day. Table 1 captures how many of them picked up the radio reminder calls.

Table 1 here

4.3. Radio spillovers and information sharing

Because the radio messages were broadcasted several times during the day and it was impossible to exclude non-treated farmers from listening to the local radio stations, there is a concern that farmers in the control group or other treatment groups also heard the radio messages. To estimate the extent of the spillover of the radio treatment, farmers were asked whether they had heard the radio messages regarding the timing of fertilizer application of DAP and urea at end-line.[8] Aside from farmers assigned to the radio treatment, only 16 other farmers answered positively (3 control farmers, 3 farmers from the extension training treatment, and 10 farmers from the IVR treatment). We therefore expect that the spillover from the radio messages was minimal.

The endline survey collected additional data on possible spillover effects coming from farmers sharing the information they learned. Participating farmers were asked whether they had shared any of the recommendations they received with their friends, neighbours or relatives.[9] Approximately 36% of participants report sharing recommendations with others. Unfortunately, given our study design, we cannot estimate the effect of this information on our estimates, though this is an interesting avenue for future research. Furthermore, most farmers in the app treatment (76%) accessed the smartphone app on their own smartphone but the remaining 24% of farmers accessed the information from a smartphone owned by a member of the household or neighbour.

4.4. Balanced test for controls

To test whether randomization constructed observationally equivalent groups, we check that key variables of interest at baseline are balanced by regressing baseline variables on binary treatment

[8] The question asked was "Were any of the CIMMYT radio messages you listened to about the optimal timing of fertilizer application on maize (like which fertilizers to apply, when and how to apply them)?"
[9] "Did you share any of the recommendations regarding maize timing of fertilizer application provided by CIMMYT with your friends and neighbors?"

assignment indicators. The results are shown in Table 2, Columns 1 to 4. Column 5 reports the sample mean and standard deviation. As observed from Table 2, a number of baseline variables including high school level, head of household gender, dependency ratio, asset index[10] and age of respondent are imbalanced. We therefore include these as regression controls, *X*, in equation 1 and 2 above. We report results both with and without these controls. Table 2 also shows that more farmers assigned to the app treatment applied fertilizers after planting in 2017 compared to the other treatment and control groups. Similarly, farmers randomly assigned in the extension training treatment group apply significantly less fertilizers at planting compared to the rest of the groups. These imbalances likely exist because assignment to treatment was done at the cooperative-level, and that there exist significant differences across cooperatives.

Table 2 here

4.5. Balanced test for outcome variables

We check whether the outcome variables of interest outlined above are balanced between the treatment and control groups at baseline. General agronomic literacy, urea applied at v6 and v10, and DAP applied at planting are again not well balanced across all treatments (Table 3). Regarding agronomic literacy, this imbalance does not affect the analysis since we are most interested in the knowledge acquired through the treatments, captured by the relevant agronomic score, which is

[10] We construct an asset index following Sahn and Stifel (2000) using factor analysis with data collected at baseline regarding farmers' ownership of livestock, durables and productive assets. We generate three asset indices, a durables asset index (bicycle, gas cooker, radio, television, etc.), a livestock asset index (goats, sheep, buffalo, etc.), and a productive asset index (barrel, chain saw, sickle, etc.), as well as an aggregate index encompassing all three groups. Factor summary statistics for each asset owned by the respondents comprising the asset indices are reported in Appendix H, Table H.1. The estimated factor loadings and summary statistics for each asset index by percentiles are also available in Appendix H, Tables H.2 and H.3, respectively.

balanced. Concerning the adoption outcomes, a greater number of farmers in the app and radio treatments were already splitting urea application in two doses, at v6 and v10, and a greater number of farmers in the IVR and extension training treatments were applying DAP only at planting compared to the rest of the treatments, before the intervention.[11]

Table 3 here

These imbalances, however, are driven by few observations. Only a total of 19 farmers were counting leaves to identify v6 and v10 stages prior to treatment[12]. In the following analysis, we report our findings including the entire sample. However, we also estimate the ITT when dropping these 19 farmers and our results are impervious to dropping these observations, as discussed in Section 5.2.

5. Results

The results measuring the effects of the treatments on agronomic knowledge and adoption rates are presented in Tables 4, 5, 6 and 7. Columns (1) to (4) in each of these tables display the regressions with and without controls for the knowledge outcomes (i.e., general and relevant agronomic test scores) and columns (5) to (8) display the equivalent estimations for the adoption outcomes (i.e. urea at v6 and v10, DAP at planting). Our preferred specification includes

[11] We also test whether these imbalances were driven by a particular district and do not find that they were.
[12] 5, 11, 0, 1, and 2 farmers in the radio, smartphone app, extension training, IVR and control treatments, respectively.

unbalanced baseline controls, columns (2), (4), (6) and (8) but we report here results both with and without controls for completeness.

Agronomic literacy scores

Farmers in the smartphone app treatment and in-person extension training achieved between 6 to 9% higher percentage scores in the general and relevant agronomic test scores, respectively, compared to control farmers, at the 5% and 1% statistical levels of significance (columns (2) and (4) of Table 4) and the extension training at the 10% and 5% levels of significance (columns (2) and (4) of Table 6). Both these results are robust with and without controls. We find no statistically significant effects on knowledge outcomes for the Radio and IVR treatments (Tables 5 and 7). We must note, however, that we do find a small but positive effect of the radio treatment on the relevant agronomic literacy score, albeit statistically insignificant. The lack of significance may result from being underpowered. Indeed, the sample size needed to detect a 3-point increase in the relevant agronomic test score (column 3 Table 5), is 2,658 observations[13]. When comparing the treatments together (Table 8), these results hold with the same coefficient magnitudes and levels of significance. Comparing the difference in relevant agronomic test scores across treatments, the smartphone app and the extension training outperform the IVR treatment with an effect in test scores being 7 to 10 percentage points greater than the IVR effect, statistically significant at the 10% level. However, the difference between the smartphone app and extension training compared to the radio is not statistically significant. Likewise, the smartphone app is not statistically different from the extension training.

[13] We use Stata's power command: "power twomeans 36.24 38.64, sd1(20.04) sd2(22.25) power(0.8) alpha(0.05) nratio(2)".

Tables 4-8 here

Adoption rates

Both the smartphone app and the extension training have positive and statistically significant effects (at the 1% and 5% confidence levels, respectively) on the urea top dressing application, consistent with and without controls, however we find no significant effect in any of the treatments for DAP at planting (Tables 4-7 columns (7)-(8)). Farmers randomly assigned to the smartphone app treatment are 6% more likely to adopt the urea recommendations on their maize plots compared to farmers in the control group at the 5% level of significance (Table 4 column (6) and Table 8 column (6)). The extension training increases the likelihood of adoption of urea recommendations by 10% compared to farmers in the control group at the 5% level of significance (Table 6 column (6) and Table 8 column (6)). The IVR and radio treatments do not have a statistically significant effect on inducing adoption of the recommended urea practices. When comparing the effect across treatments (Table 8), we find no statistical difference among them. We also test whether the treatments may have had an effect on total fertilizer use, and only find a positive and statistically significant effect of the radio treatment (results available from the corresponding author by request). The treatments therefore mostly incited farmers to change the timing of fertilizers applied, as was intended by the treatment, and not the total quantity of fertilizer applied. Finally, we conducted an analysis on the impact of treatment on farmers' yields, however, the results are considerably noisy and inconsistent across regression specifications, likely due to significant self-reported yield errors.

Agronomic literacy scores and adoption

We are also interested in examining the relationship between knowledge and adoption. To do so, we estimate the following two-stage least squares model, where we control for the likely endogeneity of higher test scores with the treatment variables shown to affect test scores, i.e., farmers receiving the smartphone app and extension treatments:

$$Y_{ic}^{endline} = \alpha_0 + \mu_1 Y_{ic}^{baseline} + \mu_2 \widehat{K_{ic}} + \gamma X + \varepsilon_{ic} \quad (3)$$

$$K_{ic} = \alpha_1 + \mu_3 Y_{ic}^{baseline} + \Lambda' Z_{ic} + \gamma X + \nu_{ic} \ (4)$$

The variables are the same as those denoted in equations (1) and (2) in Section 4 above. K_{ic} denotes the knowledge score of farmer i in cooperative c and Z_{ic} are the instrumental variables, dummies for farmers receiving the smartphone app and extension treatments[14]. As can be seen in Table 9, the relevant agronomic test score is positively associated with applying urea at v6 and v10, statistically significant at the 1% level, suggesting that the ability to retain information will lead to a higher likelihood of adopting the recommended practice of applying urea application at v6 and v10. The first stage is reported in Appendix F.

5.1. Heterogeneous effects

We are interested in investigating the heterogeneous effects of the treatments to better understand how different communication technologies might distinctly affect women and lower income households. Indeed, with the migration of many men looking for employment opportunities in neighboring countries, women are left with managing the farm (Slavchevska et al., 2020).

[14] The first stage results, not reported here, but available from the corresponding author by request, reveal that the smartphone app and extension treatments are positively correlated with knowledge.

Likewise, worst off farmers may respond differently to different technologies. Therefore, knowing how these particular groups of farmers respond to different technologies has important policy implications, i.e., different ICTs may be better suited to reach women and/or lower income cell-owning farmers.

We use the same specification as in equation (2) but interact treatments with gender and wealth dummy variables to measure the heterogeneity of the treatment effects by gender and wealth, respectively. For gender, the dummy variable equals 1 if the respondent is female or 0 if the respondent is male and for wealth two dummy variables were generated using our wealth asset index, *poorest* and *richest*, separating farmers into two income categories, below the bottom 25th income quartile for *poorest* (Yes=1; 0 otherwise) and above the 75th income quartile for *richest* (Yes=1; 0 otherwise).

Gender

The effects of the treatments on agronomic test scores by gender are presented in Table 10, learning outcomes among treated females are not significant, except for the IVR where female farmers in the IVR achieved 6.8 to 10.7% lower test scores than men in the same treatment at the at the 10 and 5% levels of significance, respectively (columns (1), (3) and (4)). Regarding adoption outcomes, female farmers are on average approximately 7.4% more likely to adopt the urea recommendations compared to men in the radio treatment, statistically significant at the 10% level (column (6)). Similarly, columns (5) to (6) also show that women are 7.8% less likely to adopt urea recommendations in the smartphone app (10% level of significance). The bottom of Table 10 shows the total effects by gender.

Table 10 here

Wealth

The effects for the poorest farmers are presented in Table 11. From the regression in column (3), poorer farmers in the sample are on average 7% less likely to adopt the urea recommendations relative to farmers in higher income quartiles, statistically significant at the 1% level, but we see that this effect is not driven by any particular treatment. Interestingly, poorest farmers seem to achieve 11.7% higher relevant agronomic test scores from the IVR treatments relative to wealthier farmers at the 5% confidence (column (4)). This seems to be the case for the radio treatment as well, whereby farmers achieve 10.1% higher relevant agronomic test scores. However, these results no longer hold when including controls (column (4)). The smartphone app and the extension training treatment have no significant differential effects.

Table 11 here

The richest farmers in the smartphone app treatment are 8% less likely to split the application of urea as suggested, compared to the rest of the farmers who received the smartphone app and belong to a lower income quartile (significant at the 1% level (Table 12, column (6)). Similar effects were found for the extension training treatment where wealthier farmers are on average 10.8% less likely to adopt urea recommendations as a result of attending the in-person extension training compared to the rest of farmers who attended the same training (those below the 75th income quartile), significant at the 10% confidence level (Table 12, column 3). Interestingly, the radio and IVR treatments also seem to be less effective in inducing knowledge outcomes for wealthier farmers, reducing both general and relevant agronomic test scores between 6 and 13%, respectively (Table 12, columns (1)-(4)).[15]

Table 12 here

5.2. Robustness Checks

We test the robustness of our results by estimating the ITT effects using first differences in lieu of the analysis of covariance (ANCOVA) specification in equation (1) above. We find similar magnitudes in the coefficients and statistical significance as shown in Table G.1, Appendix G. Finally, when removing the 19 farmers who applied urea at v6 and v10 at baseline the results still hold (Tables G.2 in Appendix G). We also estimate the average treatment effect on the treated and again find that our results hold (available from the corresponding author by request).

Adjusted p-values

We calculate Romano-Wolf adjusted p-values to correct for the familywise error rate (FWER), the probability of making at least one false discovery among a family of comparisons. We also provide the p-values for randomization inference and present these corrections alongside the unadjusted p-values from the regression in equation (1) (Table 13). Our findings are robust to the correction for multiple hypothesis testing, the p-values for randomization inference are identical to the unadjusted p-values at the nearest decimal across all specifications. The Romano-Wolf FWER adjusted p-value, however, presents some discrepancies on knowledge outcome regressions and

[15] We also estimate a regression with poorer and better off households estimated jointly (interacted with treatments) (available from the authors by request). Our estimates in this joint estimation only hold for the better off households.

urea v6 and v10 for the IVR treatment (column (4)), as well as for adoption outcomes for the radio and smartphone app (columns (1) and (2)).

Table 13 here

6. Discussion

6.1 Summary of results

In comparing the effectiveness of different ICT treatments in fostering knowledge and adoption of new agricultural practices, we find that the smartphone app and extension training are the most effective tools. In particular, the smartphone app increased agronomic knowledge test scores by 7.8%, and increased the likelihood of adoption of the urea recommendations by 8.4%, relative to the control group. Extension training was also effective, increasing the probability of adopting the urea recommendations by 13% compared to the control group, but its effect on knowledge was not robust across all regression specifications. Conversely, the radio treatment had no significant impact on farmer knowledge or adoption of the improved fertilizer application practices. An important caveat to this finding is that the study could not extrapolate the effects of the radio treatment alone since we implemented it in conjunction with IVR reminders to tune into the radio. While the IVR messages were reminders to tune into the radio program, wholly separate from the IVR experimental treatment, messages sent via the IVR platform were a part of the radio program experience.

We find male respondents to be more likely to adopt information transmitted via newer technologies (i.e., apps and IVR). We find no evidence of exclusion of female farmers from technologies, since all female farmer participants in our sample owned a smartphone, with the exception of 5 female farmers who accessed a phone from a third party. Approximately 48.2% of our baseline respondents were female, and 41.8% of smartphone app users in the survey were female. Female farmers in our sample were on average 13% less able of opening apps on their smartphones[16] compared to male farmers[17], statistically significant at the 1% level. The observed differences in smartphone literacy and app usage between male and female farmers in our sample may help explain why we find the smartphone app was not as effective among female farmers compared to men. However, we note that the differential treatment impact of the app on literacy scores by gender is less than on adoption, suggesting that there are likely other reasons for the lack of adoption by females, e.g. lack of access to inputs and/or credit.

Phone ownership is important as it could differentially impact treatment uptake. For example, borrowing a neighbor's phone to access the smartphone app might be easier than coordinating a time to access the phone at specific times for the radio and IVR treatments. This might help explain the lower treatment impact on the IVR and radio treatments. However, because we find that almost all members owned a phone, 98.65 % owned a phone, 77.5% of which were smartphones, and IVR and radio messages could be transmitted via smartphones or non-smartphones, we do not expect phone ownership to differentially affect treatment uptake. We find better-off farmers were less likely to adopt new farming practices regarding urea in the smartphone app and extension training treatments. In the end-line survey, respondents cited one of the main causes for not adopting the recommendations was that the information was not detailed enough, suggesting a demand for more diversified and tailored agricultural information from ICT tools.

[16] Farmers were asked to perform a short test during the baseline survey to check whether they could open an app on their smartphones. The enumerators then rated their performance selecting one of the following options: "Easily", "With difficulty", "Could not".
[17] Regressions controlling for whether farmers could open an app on their smartphones at baseline are available upon request. We note that our regression results remain unchanged.

Similar results have been found in studies using mobile services for agricultural development in India and Uganda where the poorest farmers gained more from the intervention than those who are better off since wealthier farmers likely had access to better services and traders to access information (Muto and Yamano, 2009; Fu and Aker, 2016).

6.2 The role of trust

To better understand our results and why certain technologies were more appealing to certain groups within our sample, we examine some of the distinguishing features of these technologies that might affect adoption. We decompose the different ICTs by some of their key attributes, e.g., visual features, auditive features, field demonstrations, in-person delivery, timely exposure, frequent access, and accessibility to illiterate people, shown in Table Appendix I1. Since we cannot isolate any of these features, we cannot explicitly test the degree to which these attributes affect adoption. In appendix I, we discuss how these different features might affect adoption. Further work that compares the same ICT with and without such features is needed to explicitly test how specific attributes affect adoption.

We did, however, ask respondents about their trust and so we can test whether different levels of trusting behavior affect the likelihood of adopting fertilizer timing management recommendations through different information channels. Higher levels of trusting and trustworthy behavior have been shown to be associated with greater economic growth and increased efficiency (Arrow, 1972; Fukuyama, 1995; Knack and Keefer, 1997; LaPorta et al., 1997). Trust has been commonly estimated via a two-stage game per Berg et al. (1995) or by survey questions. The General Social Survey (GSS) and World Values Survey (WVS) trust question, “Generally speaking, would you say that most people can be trusted or that you can’t be too careful in dealing with people?", is the most widely used question to measure trust (Glaeser et al., 2000; Naef and Schupp, 2009). However, this question has been found to elicit different responses due to different interpretations in a variety of cultural contexts stemming from the difficulty in understanding who comprises "most people", what it means to trust someone, and respondents' unwillingness to answer truthfully (Glaeser et al., 2000). Fehr (2009) creates a trust index and finds that his index is an accurate reflection of trust since it correlates with risk preferences and beliefs, showing that it is consistent with the idea that people derive their answers from introspecting on their own likely behaviors in situations requiring trust.

We measure farmers' trust levels using the trust index as created by (Fehr, 2009). The index contains all three standard questions[18] measuring trust in strangers and takes the average of the answers to all three questions. We separate the index into quartiles, and create a dummy variable called "Least trusting", taking the value of 1 if the farmer is below the 25th quartile and 0 otherwise. Replicating the same methodology used to study the heterogeneous effects of the treatments, equation 2, we interact this dummy variable with the treatments, and report the results in Table 14.

Table 14 here

Regarding DAP at planting, we, again, do not find any statistically significant effects of the treatments, or treatments conditional on trusting levels. In terms of the timing of urea application, we note that after controlling for trust, our main results hold -- the smartphone app and the extension training are overall most effective in disseminating the urea recommendations. In terms of trust, we see that least trusting farmers are more likely to adopt if the information was

[18] "In general, one can trust people", "Nowadays, you can't rely on anybody" and "When dealing with strangers, it is better to be cautious before trusting them".

transmitted via a traditional extension agent, albeit weakly statistically significant at the 10% level. In other words, least trusting farmers are less likely to adopt advice coming from newer sources. In order to better understand how gender affects the potential drivers of adoption of information communicated via different ICTs, we explore whether the trusting levels differ by gender. We do not, however, find a statistically significantly difference in the likelihood to be least trusting by gender (the mean difference is 0.016, statistically insignificant).

Finally, we must note that since CIMMYT is a well-known and established organization working in Nepal since 1985, the significant effect on extension training could in part be attributed to the familiarity and trust that farmers have in CIMMYT representatives. Indeed, higher adoption rates of information transmitted via ICTs have been found when introduced by credible organizations (Gunasekera and Miranda, 2011). Indeed, the second most popular cited reason for adopting new technologies at endline was trusting the information source[19]. Further work is needed to determine the importance of trust in an information source on farmers' decisions to adopt recommended practices. In particular, further work is needed to refine and adopt trust elicitation techniques and games to the agricultural and rural contexts in low-income countries like Nepal.

6.3 ICT costs

A final and important consideration with policy implications is comparing the cost of receiving information via these different communication channels. The only cost incurred by the farmer for participating in the study was his/her time since the implementation costs were covered by the project. The time needed to assist in-person visits from CIMMYT staff, i.e., for the smartphone

[19] The other options were "I expected higher yields", "Advice was simple (clear and easy to implement)", "Did not require purchasing additional inputs (labour and fertilizer)" and "I thought the information was interesting and I wanted to try it". The first cited reason was expecting to higher yields.

app and extension trainings, required more time than listening to IVR or radio messages from home. However, the IVR and radio messages were more frequent.

To estimate the costs of these technologies should farmers have to pay for them, we estimate the programmatic costs per farmer of running each program. The costs of producing and distributing the extension materials for the ICT-based extension methods is fixed, so that as the number of farmers reached increases, the per-farmer costs decrease. Table 15A shows the estimated per farmer costs for the different ICTs at varying levels of participation. The costs of running the extension training program are, as expected, highest to run and increase proportionally to the number of participants due to the high per farmer costs. The cheapest treatment to implement was the radio messaging, costing only USD 143 per farmer, followed by the smartphone app at 203 USD per farmer, followed by the IVR treatment at USD 246 per farmer, (when n = 886). These latter costs decrease rapidly as the number of participating farmers increase. We also estimate the costs per farmer adopting the technology, and find that given the higher adoption rate of app users, the app becomes the most cost-effective tool when looking at the cost per farmer adopting a technology. Finally, we compare the costs per female and male farmer adopting practices disseminated via different technologies. Given the adoption findings above in Table 10, we see that it is more cost effective at small scales to support females' adoption of practices through extension rather than IVR, and that it is more cost effective to reach male farmers through an app than other ICTs.

Table 15A and 15B here

Given these cost estimates, we can compare the estimated benefits of adopting the recommended practices using crude, back-of-the-envelope calculations. Using an average maize plot size of

0.234 ha, an estimated average increase of 2T/ha[20] from adopting the recommended practices, and a mean maize producer price of 262.2$/T[21], we calculate a benefit of $122.24/farmer adopting the practice. Therefore, the benefits of the app treatment, for example, exceed its costs per farmer when interventions fall somewhere between 10,000 and 50,000 participants. The number of participants must increase for benefits to exceed costs for female respondents, given their lower adoption rates. Of course, these estimations are sensitive to the other parameters, i.e., the estimated increase in yields from treatment, the price of maize, and average plot size, but nonetheless, we see that benefits of ICTs exceed their costs at fairly large scales, and that the costs of extension training are very high relative to its benefit. As we discuss further below, since public agricultural extension programs exist anyway, adding complementary digital support tools could improve efficiency in terms of farmer reach and impact per dollar spent.

6.4. Study Limitations

This study has certain limitations that can help guide interesting and useful avenues for future research. As aforementioned, this is the first study we are aware of that compares different ICTs to each other. While useful to examine and compare different ICTs to each other, it is likely that a package of two or more ICTs would be most beneficial in inducing behavioral change in technology adoption. Due to budgetary constraints, we could not test how two or more of these tools used together might affect the adoption and retention of information. Further work is needed in this domain. Furthermore, isolating our radio messages to the subgroup of farmers in that treatment group was a challenge as farmers from other treatments could potentially hear the messages if they were listening to the radio at that moment. While we took certain measures to

[20] These were obtained from the CIMMYT field trials.
[21] This is the average producer price for maize in Nepal between 2016 and 2022, obtained from the Food and Agricultural Organization's FAOSTAT, last accessed online April 29, 2022.

minimize this treatment spillover, we may still be under-reporting our radio treatment effect. Additionally, as aforementioned, eliciting trust among respondents proved difficult. The enumerators conducting the surveys reported that respondents had a difficult time understanding the meaning of the trust questions and how to answer them. Further work is needed to better measure trust in a rural, agricultural setting before measuring how it affects farmers' attitude towards new information. Finally, further work is needed to explore the degree to which social desirability bias, response bias, and the Hawthorne effect might be driving our results. Indeed, farmers who received phone calls from CIMMYT inviting them to participate in the study might feel they are being closely followed and therefore act differently, inducing them to respond more favorably, for example, to the self-reported outcome variables. Given our study design, we cannot explicitly test for these possible biases, but it would be an interesting avenue for future research.

7. Conclusion

Technological development is an essential component to growth in developing countries. The rapid growth of mobile phones penetration has made it one of the most rapidly adopted technologies in history and with it the potential to disseminate information to poorer and more remote populations. The widespread disruption from the COVID-19 pandemic in accessing traditional face-to-face human interactions in group settings, one of the core components of classical agricultural extension, has further demonstrated the positive potential for ICT-based agricultural advisory tools. Nonetheless, not all ICTs are alike or as effective in communicating agronomic information to farmers. Visual features, in person-interactions and timely access differentiate the smartphone app and extension training from radio and IVR, and seem to play an important role in the adoption of new agricultural practices within the context of this study. Furthermore, different features may appeal to various segments of the population. For example, we find that reaching women through traditional extension training and radio messages remains the most effective, with the app actually inducing little adoption for women. Moreover, there are different cost implications associated with different ICTs. The provision of information via mobile technology does present significant cost savings over traditional extension services.

From this study we have identified emerging questions related to better understanding how ICT-based agricultural advisory tools may fit into the farmer ecosystem. Additional work is needed to determine whether the promising results we find for information sharing via an app are externally valid. What specific ICT attributes make it successful in different contexts and for which demographic groups, e.g., poorer and/or female respondents? Additional work is also needed to assess the degree to which the technologies examined can be used synergistically to bring about more effective behavioral change. Nonetheless, our findings support the idea that there is an important role for mobile phone technologies including applications in disseminating information regarding agricultural practices.

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Figures

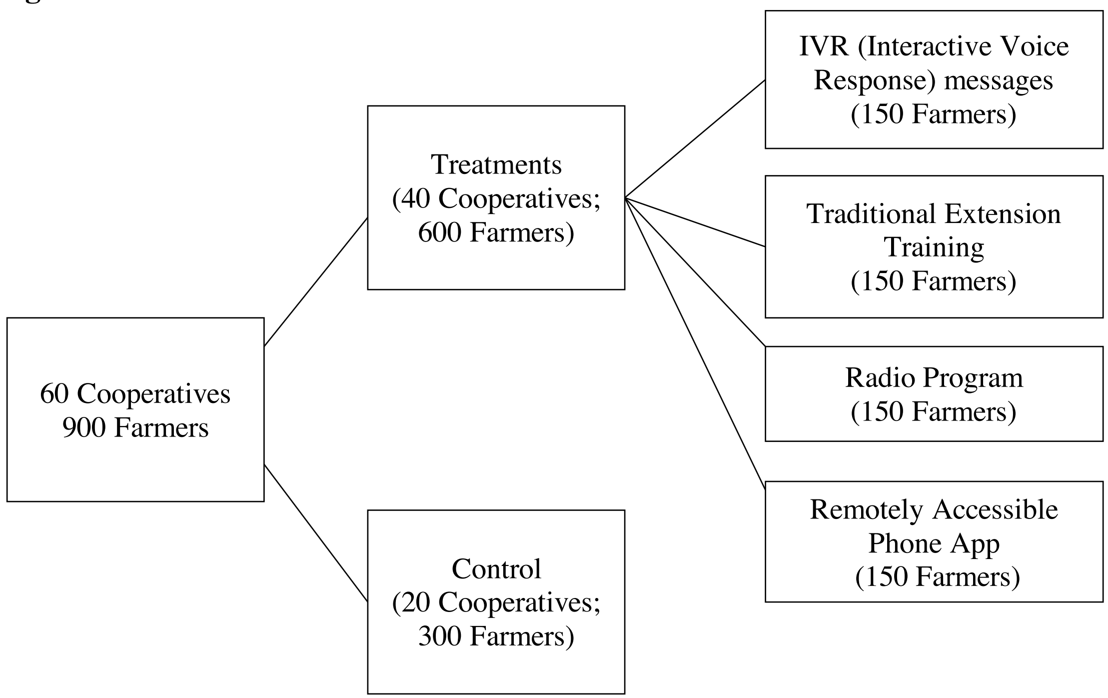

Figure 1: Treatment randomization structure

Tables

Table 1: Treatment compliance rates

Treatments	Farmers randomly assigned to the treatments	Farmers who used the treatments[1]
	(1)	(2)
1. IVR	150	140
2. Radio	150	135
3. Extension training	150	105
4. Smartphone App	150	106
TOTAL	600	445

[1]User data was estimated counting the number of farmers who attended the extension training and the smartphone app meetings, after receiving an invitation. The radio and IVR treatments usage were recovered from the data gathered by the company VIAMO, who recorded whether farmers picked up the calls for the IVR messages and the radio reminders.

Table 2: Baseline balance tests

Controls	Radio	App	Training	IVR	Sample Mean	N
	(1)	(2)	(3)	(4)	(5)	(6)
Age of respondent	-0.821	0.249	-3.370**	-0.458	44.051	881
	(1.338)	(1.347)	(1.323)	(1.338)	(13.2487)	
High School and above (Yes=1)	0.142***	0.058	0.106**	0.119**	0.380	900
	(0.048)	(0.049)	(0.048)	(0.048)	(0.486)	
No education (Yes=1)	-0.001	-0.080*	-0.095**	-0.049	0.218	900
	(0.041)	(0.041)	(0.041)	(0.041)	(0.413)	
Female Head (Yes=1)	-0.021	-0.080**	-0.148***	-0.042	0.207	900
	(0.040)	(0.040)	(0.040)	(0.040)	(0.405)	
Dependency Ratio	-0.045**	-0.068***	-0.086***	-0.047**	0.379	885
	(0.022)	(0.022)	(0.021)	(0.022)	(0.216)	
Married (Yes=1)	0.020	0.020	0.014	0.014	0.905	900
	(0.030)	(0.030)	(0.029)	(0.029)	(0.293)	
Fertilizer at planting (Yes=1)	-0.010	0.003	-0.103***	0.003	0.979	886
	(0.014)	(0.014)	(0.014)	(0.014)	(0.145)	
Fertilizer after planting (Yes=1)	0.014	0.125**	-0.041	0.021	0.577	886
	(0.050)	(0.050)	(0.049)	(0.050)	(0.494)	
Smartphones owned by the household	0.097	0.185	0.003	-0.090	2.043	900
	(0.120)	(0.120)	(0.120)	(0.120)	(1.205)	
Maize yields from main maize plot 2017 (kg/ha)	1447.155	1095.414	193.850	-256.131	3944.281	898
	(1.930)	(1.460)	(0.260)	(0.340)	(7514.372)	
Area main maize plot 2017	-0.031	0.045	0.056	0.014	0.234	900
	(0.770)	(1.090)	(1.360)	(0.340)	(0.166)	
Land ownership (ha)	-0.032	0.040	0.012	-0.054	0.550	886

	(0.043)	(0.043)	(0.042)	(0.043)	(0.415)	
Wealth asset index	0.140	-0.22**	0.002	0.154	0.006	886
	(0.101)	(0.101)	(0.100)	(0.101)	(1.001)	

Table 2 reports the baseline balance tests between the treatment groups, columns (1)-(4). The estimations were derived from an OLS linear regression model regressing each covariate at baseline against the treatment dummy variables. Standard errors are presented in brackets below the coefficients. The significance reported corresponds to statistically significant differences in the covariate means between the treatment groups and the control group at baseline. Column 5 provides the sample mean and standard deviation in brackets at baseline. *p<0.1; **p<0.05; *** p<0.01.

Table 3: Balanced test for outcome variables

Variables	Radio	App	Training	IVR	Sample Mean	N
	(1)	(2)	(3)	(4)	(5)	(6)
Relevant agronomic score (%)	1.4877	1.881	-0.537	2.5081	-0.394	886
	(2.0233)	(2.0326)	(2.0053)	(2.0233)	(23.716)	
General agronomic score (%)	1.5285	3.3322**	1.9477	1.7759	2.795	886
	(1.5407)	(1.5478)	(1.527)	(1.5407)	(18.232)	
UREA applied at v6 and v10	0.0273*	0.0691***	-0.0068	0	0.03	886
	(0.0144)	(0.0145)	(0.0143)	(0.0144)	(0.172)	
DAP applied at planting	0.0179	-0.0009	-0.0588*	0.0587*	0.091	886
	(0.0336)	(0.0337)	(0.0333)	(0.0336)	(0.288)	

Table 3 reports the balanced tests between the treatment groups, columns (1)-(4)). The estimations come from an OLS linear regression model regressing each outcome variable at baseline against the treatment dummies. Standard errors are presented in brackets below the coefficients. The significance reported corresponds to statistically significant differences in the outcome variable means between the treatments and control groups at baseline. Column 5 provides the sample mean and standard deviation in brackets at baseline. *p<0.1; **p<0.05; *** p<0.01.

Table 4: Smartphone app treatment effect on knowledge and adoption outcomes

Explanatory Variables	**Dependent Variables (ANCOVA)**							
	General Agronomic Literacy Test Scores	**General Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Urea at v6 and v10**	**Urea at v6 and v10**	**DAP at planting**	**DAP at planting**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Smartphone App	6.162***	5.600**	9.020***	8.822***	0.061**	0.059**	0.048	0.055
	(2.052)	(2.046)	(2.86)	(2.956)	(0.027)	(0.028)	(0.067)	(0.068)
General Agronomic Score Baseline	0.448***	0.415***						
	(0.07)	(0.077)						
Relevant Agronomic Score Baseline			0.294***	0.282***				
			(0.066)	(0.07)				
Urea v6v10 Baseline					0.072*	0.06		
					(0.042)	(0.036)		
DAP at planting Baseline							0.315***	0.307***
							(0.086)	(0.08)
Endline Control Group Mean	27.49	27.49	34.97	34.97	0.03	0.03	0.15	0.15
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.158	0.185	0.109	0.126	0.022	0.028	0.084	0.096
N	441	438	441	438	441	438	441	438

Table 4 reports the ANCOVA estimates of the impact of the Smartphone App treatment on knowledge and adoption outcomes. Standard errors are presented in parentheses below the coefficients. The statistical significance reported in columns (1)-(4), corresponds to the statistically significant effects of the Smartphone App in percent change in agronomic test scores (over 100%) relative to control farmers and the ones in columns (5)-(8) correspond to the effect of the Smartphone App in inducing a one-step change in the likelihood of adopting the recommended practices compared to the control. All the regressions use clustered standard errors at the cooperative level. *p<0.1; **p<0.05; *** p<0.01.

Table 5: Radio treatment effect on knowledge and adoption outcomes

Explanatory Variables	**Dependent Variables (ANCOVA)**							
	General Agronomic Literacy Test Scores	**General Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Urea at v6 and v10**	**Urea at v6 and v10**	**DAP at planting**	**DAP at planting**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Radio	2.613	2.353	3.299	3.037	0.018	0.024	0.032	0.015
	(2.342)	(2.213)	(3.322)	(3.154)	(0.025)	(0.025)	(0.063)	(0.06)
General Agronomic Score Baseline	0.537***	0.499***						
	(0.071)	(0.08)						
Relevant Agronomic Score Baseline			0.343***	0.320***				
			(0.05)	(0.057)				
Urea v6v10 Baseline					-0.044**	-0.028**		
					(0.017)	(0.011)		
DAP at planting Baseline							0.333***	0.322***
							(0.079)	(0.074)
Endline Control Group Mean	27.49	27.49	34.97	34.97	0.03	0.03	0.15	0.15
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.182	0.206	0.106	0.125	0.003	0.016	0.097	0.117
N	443	440	443	440	443	440	443	440

Table 5 reports the ANCOVA estimates of the impact of the Radio treatment on knowledge and adoption outcomes. Standard errors are presented in parentheses below the coefficients. The statistical significance reported in columns (1)-(4), corresponds to the statistically significant effects of the Radio in percent change in agronomic test scores (over 100%) relative to control farmers and the ones in columns (5)-(8) correspond to the effect of the Radio in inducing a one-step change in the likelihood of adopting the recommended practices compared to the control. All the regressions use clustered standard errors at the cooperative level. *p<0.1; **p<0.05; *** p<0.01.

Table 6: Training treatment effect on knowledge and adoption outcomes

Explanatory Variables	**Dependent Variables (ANCOVA)**							
	General Agronomic Literacy Test Scores	**General Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Urea at v6 and v10**	**Urea at v6 and v10**	**DAP at planting**	**DAP at planting**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Extension Training	6.345*	5.511*	9.540**	8.514**	0.104**	0.102**	0.024	0.014
	(3.297)	(3.033)	(3.846)	(3.722)	(0.045)	(0.039)	(0.067)	(0.067)
General Agronomic Score Baseline	0.511***	0.462***						
	(0.066)	(0.077)						
Relevant Agronomic Score Baseline			0.355***	0.337***				
			(0.06)	(0.065)				
Urea v6v10 Baseline					-0.027*	-0.041**		
					(0.014)	(0.02)		
DAP at planting Baseline							0.335***	0.328***
							(0.114)	(0.11)
Endline Control Group Mean	27.49	27.49	34.97	34.97	0.03	0.03	0.15	0.15
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.188	0.215	0.128	0.145	0.04	0.054	0.086	0.094
N	447	446	447	446	447	446	447	446

Table 6 reports the ANCOVA estimates of the impact of the Training treatment on knowledge and adoption outcomes. Standard errors are presented in parentheses below the coefficients. The statistical significance reported in columns (1)-(4), corresponds to the statistically significant effects of the Training in percent change in agronomic test scores (over 100%) relative to control farmers and the ones in columns (5)-(8) correspond to the effect of the Training in inducing a one-step change in the likelihood of adopting the recommended practices compared to the control. All the regressions use clustered standard errors at the cooperative level. *p<0.1; **p<0.05; *** p<0.01.

Table 7: IVR treatment effect on knowledge and adoption outcome

Explanatory Variables	**Dependent Variables (ANCOVA)**							
	General Agronomic Literacy Test Scores	**General Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Urea at v6 and v10**	**Urea at v6 and v10**	**DAP at planting**	**DAP at planting**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IVR	-1.26	-1.65	-2.89	-3.44	0.02	0.02	0.00	-0.01
	(2.342)	(2.035)	(3.789)	(3.407)	(0.034)	(0.033)	(0.057)	(0.056)
General Agronomic Score Baseline	0.484***	0.400***						
	(0.066)	(0.079)						
Relevant Agronomic Score Baseline			0.322***	0.278***				
			(0.061)	(0.069)				
Urea v6v10 Baseline					-0.036**	-0.035*		
					(0.016)	(0.019)		
DAP at planting Baseline							0.298***	0.304***
							(0.076)	(0.071)
Endline Control Group Mean	27.49	27.49	34.97	34.97	0.03	0.03	0.15	0.15
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.15	0.198	0.089	0.136	0.002	0.029	0.086	0.105
N	443	441	443	441	443	441	443	441

Table 7 reports the ANCOVA estimates of the impact of the IVR treatment on knowledge and adoption outcomes. Standard errors are presented in parentheses below the coefficients. The statistical significance reported in columns (1)-(4), corresponds to the statistically significant effects of the IVR in percent change in agronomic test scores (over 100%) relative to control farmers and the ones in columns (5)-(8) correspond to the effect of the IVR in inducing a one-step change in the likelihood of adopting the recommended practices compared to the control. All the regressions use clustered standard errors at the cooperative level. *p<0.1; **p<0.05; *** p<0.01.

Table 8: Treatment effects on knowledge and adoption outcomes

	Dependent Variables (ANCOVA)							
	General Agronomic Literacy Test Scores	**General Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Urea at v6 and v10**	**Urea at v6 and v10**	**DAP at planting**	**DAP at planting**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Smartphone App	6.044***	5.188**	9.031***	7.964***	0.064**	0.060**	0.05	0.05
	(2.018)	(1.971)	(2.846)	(2.847)	(0.028)	(0.027)	(0.067)	(0.067)
Radio	2.70	2.37	3.38	3.06	0.02	0.02	0.03	0.02
	(2.373)	(2.128)	(3.375)	(3.073)	(0.025)	(0.025)	(0.063)	(0.06)
IVR	-1.26	-1.58	-2.81	-3.16	0.02	0.02	0.00	-0.01
	(2.331)	(1.953)	(3.851)	(3.369)	(0.033)	(0.032)	(0.055)	(0.054)
Extension Training	6.400*	5.471*	9.505**	8.080**	0.102**	0.096**	0.03	0.01
	(3.314)	(2.982)	(3.961)	(3.703)	(0.043)	(0.041)	(0.067)	(0.067)
General Agronomic Score Baseline	0.483***	0.401***						
	(0.045)	(0.05)						
Relevant Agronomic Score Baseline			0.289***	0.246***				
			(0.043)	(0.045)				
Urea v6v10 Baseline					0.03	0.02		
					(0.031)	(0.027)		
DAP at planting Baseline							0.311***	0.314***
							(0.054)	(0.051)
Endline Control Group Mean	27.49	27.49	34.97	34.97	0.03	0.03	0.15	0.15
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.19	0.23	0.11	0.15	0.02	0.03	0.08	0.09
N	886.00	880.00	886.00	880.00	886.00	880.00	886.00	880.00

Table 8 reports the ANCOVA estimates of the impact of the treatments on knowledge (columns (1)-(4)) and adoption (columns (5)-(8)) outcomes, with and without controls. Standard errors are presented in parentheses below the coefficients. The statistical significance reported corresponds to the statistically significant effects by the treatments in percent change in agronomic test scores (over 100%) for columns (1)-(4), and one step changes in the likelihood of adopting the recommended practices relative to control farmers in columns (5)-(8). All the regressions use clustered standard errors at the cooperative level. *p<0.1; **p<0.05; *** p<0.01.

Table 9. The effect of knowledge scores on adoption

	Urea at v6 and v10	**Urea at v6 and v10**
	(1)	(2)
Relevant Agronomic Literacy Test Scores	0.063***	0.063***
	(0.02)	(0.02)
Urea v6v10 Baseline	-0.065	-0.052
	(0.07)	(0.07)
Controls	No	Yes
Observations	886	880

Table 9 reports the instrumental regression estimates of the impact of knowledge (measured by the relevant agronomic literacy test score at endline) on adoption of Urea at v6 and v10 without controls in column (1) and with controls in column (2). Standard errors are presented in parentheses below the coefficients. The statistical significance reported corresponds to one step changes in the likelihood of adopting the recommended practices relative to control farmers. *p<0.1; **p<0.05; *** p<0.01.

Table 10: Treatment effects by gender

Explanatory Variables	**Dependent Variables (ANCOVA)**							
	General Agronomic Literacy Test Scores	**General Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Urea at v6 and v10**	**Urea at v6 and v10**	**DAP at planting**	**DAP at planting**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Smartphone App	6.982**	5.867*	10.130**	9.019**	0.094***	0.093***	0.07	0.08
	(3.14)	(3.24)	(3.89)	(3.90)	(0.03)	(0.03)	(0.08)	(0.08)
Radio	2.96	2.08	3.95	3.13	-0.03	-0.02	0.1	0.1
	(3.37)	(3.18)	(4.09)	(3.92)	(0.02)	(0.02)	(0.08)	(0.08)
IVR	1.01	0.02	1.21	0.28	0.04	0.05	0.03	0.03
	(3.17)	(2.82)	(4.34)	(4.04)	(0.05)	(0.05)	(0.08)	(0.08)
Extension Training	5.92	4.83	8.803*	7.441*	0.082*	0.080**	0.06	0.06
	(4.27)	(4.00)	(4.60)	(4.26)	(0.04)	(0.04)	(0.08)	(0.08)
Female (Yes=1)	-1.51	-0.68	-0.43	1.24	0.01	0.02	0.04	0.05
	(2.62)	(2.45)	(2.92)	(2.71)	(0.02)	(0.02)	(0.05)	(0.05)
App*Female	-3.13	-1.85	-3.05	-1.9	-0.076*	-0.078*	-0.03	-0.04
	(3.53)	(3.73)	(4.07)	(4.44)	(0.04)	(0.04)	(0.06)	(0.06)
Radio*Female	-0.49	0.59	-0.99	-0.01	0.078*	0.074*	-0.12	-0.13
	(3.39)	(3.46)	(3.88)	(3.84)	(0.04)	(0.04)	(0.08)	(0.08)
IVR*Female	-6.768*	-4.36	-10.749**	-8.170*	-0.054	-0.059	-0.047	-0.067
	(3.91)	(3.95)	(4.84)	(4.85)	(0.04)	(0.05)	(0.10)	(0.10)
Training*Female	0.28	1.691	1.764	3.116	0.069*	0.064*	-0.069	-0.089
	(4.18)	(4.14)	(3.99)	(3.88)	(0.04)	(0.04)	(0.07)	(0.08)
General Agronomic Score Baseline	0.463***	0.396***						

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(0.05)	(0.05)						
Relevant Agronomic Score Baseline			0.279***	0.239***				
			(0.04)	(0.05)				
Urea v6v10 Baseline					0.04	0.03		
					(0.03)	(0.03)		
DAP at planting Baseline							0.310***	0.313***
							(0.06)	(0.05)
Endline Control Group Mean	27.49	27.49	34.97	34.97	0.03	0.03	0.145	0.145
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.198	0.234	0.124	0.16	0.037	0.047	0.084	0.093
N	886	880	886	880	886	880	886	880
Total App Effect for Females	2.342	3.337	6.65	8.359	0.028	0.035	0.08	0.09
Total App Effect for Males	6.982	5.867	10.13	9.019	0.094	0.093	0.07	0.08
Total Radio Effect for Females	0.96	1.99	2.53	4.36	0.058	0.074	0.02	0.02
Total Radio Effect for Males	2.96	2.08	3.95	3.13	-0.03	-0.02	0.1	0.1
Total IVR Effect for Females	-7.268	-5.02	-9.969	-6.65	-0.004	0.011	0.023	0.013
Total IVR Effect for Males	1.01	0.02	1.21	0.28	0.04	0.05	0.03	0.03
Total Training Effect for Females	4.69	5.841	10.137	11.797	0.161	0.164	0.031	0.021
Total Training Effect for Males	5.92	4.83	8.803	7.441	0.082	0.08	0.06	0.06

Table 10 reports the impact of the treatments by gender, using ANCOVA estimations and interacting a dummy variable capturing the respondent's gender with each one of the treatment dummies. The dummy variable capturing gender is called "Female" and takes the value of 1 if the respondent is female or 0 otherwise. Standard errors are presented in parentheses below the coefficients. The significance reported has the standard interpretation and corresponds to statistically significant effects of the treatments on the outcome variables of interest, agronomic literacy test scores (columns (1)-(4)) and adoption rates (columns (5)-(8)). Statistically significant coefficients in the interaction terms denote the differential effects between female and male farmers (i.e., male is captured by the constant) on the outcomes of interest. All the regressions use clustered standard errors at the cooperative level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table 11: Treatment effects by poorest

Explanatory Variables	Dependent Variables (ANCOVA)							
	General Agronomic Literacy Test Scores	General Agronomic Literacy Test Scores	Relevant Agronomic Literacy Test Scores	Relevant Agronomic Literacy Test Scores	Urea at v6 and v10	Urea at v6 and v10	DAP at planting	DAP at planting
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Smartphone App	6.287***	5.722**	10.545***	9.669***	0.05	0.05	0.08	0.07
	(2.352)	(2.335)	(3.369)	(3.382)	(0.034)	(0.032)	(0.086)	(0.087)
Radio	1.81	1.89	1.29	1.59	0.02	0.02	0.03	0.024)
	(2.607)	(2.527)	(3.431)	(3.407)	(0.03)	(0.029)	(0.073)	(0.072)
IVR	-2.89	-2.65	-6.19	-5.81	0.01	0.02	0.03	0.02
	(2.403)	(2.301)	(3.938)	(3.809)	(0.034)	(0.031)	(0.072)	(0.074)
Extension Training	5.38	5.27	7.62	7.30	0.096*	0.094*	0.03	0.02
	(4.237)	(4.054)	(5.023)	(5.012)	(0.052)	(0.048)	(0.07)	(0.072)
Poorest (Yes=1)	2.02	-1.91	0.31	-4.98	-0.02	-0.070***	-0.02	0.00
	(2.883)	(2.839)	(3.613)	(3.664)	(0.014)	(0.024)	(0.062)	(0.058)
App*Poorest	-1.00	-1.26	-4.81	-4.33	0.04	0.05	-0.08	-0.08
	(4.236)	(4.179)	(4.512)	(4.322)	(0.055)	(0.058)	(0.095)	(0.095)
Radio*Poorest	4.55	2.46	10.122*	7.50	0.00	0.01	0.00	0.00
	(4.142)	(4.684)	(5.293)	(5.562)	(0.045)	(0.049)	(0.098)	(0.1)
IVR*Poorest	6.46	4.69	13.632**	11.708**	0.03	0.03	-0.13	-0.13
	(4.368)	(4.158)	(5.984)	(5.731)	(0.025)	(0.026)	(0.128)	(0.126)
Training*Poorest	3.22	1.20	6.36	3.99	0.02	0.02	-0.02	-0.02
	(5.221)	(4.978)	(6.339)	(6.251)	(0.05)	(0.048)	(0.081)	(0.085)
General Agronomic Score Baseline	0.448***	0.395***						
	(0.048)	(0.05)						
Relevant Agronomic Score Baseline			0.263***	0.239***				

			(0.045)	(0.045)				
Urea v6v10 Baseline					0.03	0.02		
					(0.028)	(0.027)		
DAP at planting Baseline							0.314***	0.315***
							(0.053)	(0.052)
Endline Control Group Mean	27.49	27.49	34.97	34.97	0.03	0.03	0.15	0.15
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.20	0.23	0.14	0.17	0.03	0.04	0.09	0.09
N	886	880	886	880	886	880	886	880

Table 11 reports the impact of the treatments by poorest wealth income quartile, using ANCOVA estimations and interacting a dummy variable capturing respondent wealth with each one of the treatment dummies. The dummy variable "Poorest" captures whether a farmer falls below the 25th income quartile, taking the value of 1 if yes and 0 otherwise. The statistical significance reported has the standard interpretation and corresponds to the statistically significant effects of the treatments in inducing percentage changes in agronomic literacy tests scores (columns (1)-(4)) and one step changes in the likelihood of adopting the recommended practices (columns (5)-(8)). Statistically significant coefficients in the interaction terms denote the differential effects between poorest farmers and the rest of farmers, who lie above the 25th income quartile (i.e., captured by the constant), on the outcomes of interest. All the regressions use clustered standard errors at the cooperative level. * p<0.1, ** p<0.05, *** p<0.01.

Table 12: Treatment effects by richest

Explanatory Variables	Dependent Variables (ANCOVA)							
	General Agronomic Literacy Test Scores	**General Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Relevant Agronomic Literacy Test Scores**	**Urea at v6 and v10**	**Urea at v6 and v10**	**DAP at planting**	**DAP at planting**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Smartphone App	6.965***	5.998***	10.554***	9.538***	0.071**	0.072**	0.07	0.07
	(1.89)	(1.904)	(2.855)	(2.81)	(0.029)	(0.03)	(0.067)	(0.068)
Radio	5.316**	4.139*	7.809**	6.583**	0.00	0.01	0.05	0.04
	(2.231)	(2.197)	(3.279)	(3.177)	(0.024)	(0.026)	(0.065)	(0.065)
IVR	1.15	-0.25	1.42	-0.02	0.03	0.04	0.01	0.01
	(2.562)	(2.351)	(3.974)	(3.81)	(0.045)	(0.045)	(0.048)	(0.045)
Extension Training	8.574**	6.455*	12.584***	10.129**	0.133***	0.135**	0.05	0.05
	(3.365)	(3.242)	(3.99)	(4.09)	(0.048)	(0.052)	(0.074)	(0.073)
Richest (Yes=1)	-0.90	1.35	0.88	2.66	-0.038**	-0.061**	0.10	0.03
	(2.999)	(3.369)	(4.152)	(4.493)	(0.014)	(0.028)	(0.062)	(0.057)
App*Richest	-6.55	-4.14	-10.66	-7.84	-0.071**	-0.080***	-0.14	-0.13
	(6.196)	(5.803)	(9.575)	(9.127)	(0.029)	(0.03)	(0.102)	(0.099)
Radio*Richest	-7.518**	-6.017*	-13.740***	-12.006**	0.06	0.06	-0.08	-0.07
	(3.349)	(3.442)	(5.093)	(5.158)	(0.04)	(0.039)	(0.093)	(0.09)
IVR*Richest	-6.827*	-4.73	-13.026**	-10.891*	-0.03	-0.05	-0.07	-0.08
	(3.941)	(3.837)	(6.334)	(6.215)	(0.045)	(0.047)	(0.107)	(0.105)
Training*Richest	-6.60	-3.55	-10.437*	-7.42	-0.090*	-0.108*	-0.12	-0.14
	(4.835)	(4.8)	(6.065)	(6.224)	(0.05)	(0.055)	(0.096)	(0.097)
General Agronomic Score Baseline	0.443***	0.395***						

	(0.046)	(0.048)						
Relevant Agronomic Score Baseline			0.258***	0.237***				
			(0.043)	(0.043)				
Urea v6v10 Baseline					0.02	0.02		
					(0.029)	(0.027)		
DAP at planting Baseline							0.309***	0.311***
							(0.052)	(0.05)
Endline Control Group Mean	0.03	0.03	0.05	0.05	0.06	0.06	0.06	0.06
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.21	0.23	0.15	0.17	0.04	0.05	0.09	0.09
N	886.00	880.00	886.00	880.00	886.00	880.00	886.00	880.00

Table 12 reports the effect of the experimental treatments by richest wealth income quartile, using ANCOVA estimations and interacting a dummy variable capturing respondent wealth with each one of the treatment dummies. The dummy variable "Richest" captures whether a farmer is above the 75th income quartile, taking the value of 1 if yes and 0 otherwise. Standard errors are presented in parentheses below the coefficients. The statistical significance reported has the standard interpretation and corresponds to the statistically significant effects of the treatments in inducing percentage changes in agronomic literacy tests scores (columns (1)-(4)) and one step changes in the likelihood of adopting the recommended practices (columns (5)-(8)). All the regressions use clustered standard errors at the cooperative level. * p<0.1, ** p<0.05, *** p<0.01.

Table 13: Adjusted p values

	Smartphone App	Radio	Training	IVR
	(1)	(2)	(3)	(4)
General Agronomic Literacy Test Scores				
Unadjusted p-value	0.01	0.30	0.08	0.42
Romano-WolfFWER adjusted p-value	0.00	0.24	0.004	0.87
Randomization inference adjusted p-value	0.015	0.285	0.062	0.438
Relevant Agronomic Literacy Test Scores				
Unadjusted p-value	0.01	0.34	0.03	0.32
Romano-WolfFWER adjusted p-value	0.00	0.25	0.004	0.79
Randomization inference adjusted p-value	0.011	0.329	0.038	0.319
Urea at v6 and v10				
Unadjusted p-value	0.04	0.35	0.02	0.57
Romano-WolfFWER adjusted p-value	0.02	0.54	0.004	0.79
Randomization inference adjusted p-value	0.022	0.354	0.005	0.539
DAP at planting				
Unadjusted p-value	0.42	0.81	0.84	0.82
Romano-WolfFWER adjusted p-value	0.22	0.54	0.86	0.87
Randomization inference adjusted p-value	0.39	0.78	0.86	0.83

Table 13 presents the adjusted p-values for the ANCOVA regression in equation (1) presented in the paper. The unadjusted p-values correspond to the p-values from the regressions in Tables 4-7. The Romano-WolfFWER adjusted p-values were calculated using the rwolf command on STATA and the p-values for Monte Carlo permutation tests (i.e. randomization inference adjusted p values) were performed using the Ritest command, using 1000 permutations.

Table 14. Trust and adoption rates

Explanatory Variables	Dependent Variables (ANCOVA)			
	Urea at v6 and v10	Urea at v6 and v10	DAP at planting	DAP at planting
	(1)	(2)	(3)	(4)
Smartphone App	0.077**	0.074**	0.034	0.038
	(0.036)	(0.035)	(0.071)	(0.072)
Radio	0.002	0.007	0.03	0.02
	(0.022)	(0.023)	(0.071)	(0.068)
IVR	0.022	0.025	0.014	0.003
	(0.033)	(0.033)	(0.07)	(0.068)
Extension Training	0.078**	0.073**	0.002	-0.016
	(0.034)	(0.033)	(0.062)	(0.063)
Least Trusting (Yes=1)	0.019	0.02	-0.006	-0.002
	(0.022)	(0.023)	(0.045)	(0.046)
App*Least Trusting	-0.054	-0.056	0.066	0.065
	(0.07)	(0.07)	(0.093)	(0.095)
Radio*Least Trusting	0.059	0.056	0.011	0.012
	(0.044)	(0.043)	(0.082)	(0.088)
IVR*Least Trusting	-0.017	-0.017	-0.052	-0.05
	(0.046)	(0.047)	(0.09)	(0.09)
Training*Least Trusting	0.088*	0.084	0.084	0.103
	(0.053)	(0.053)	(0.076)	(0.078)
Urea v6v10 Baseline	0.029	0.018		
	(0.028)	(0.026)		
DAP at planting Baseline			0.314***	0.316***
			(0.054)	(0.051)

Endline Control Group Mean	0.03	0.03	0.145	0.145
Controls	No	Yes	No	Yes
R-squared	0.035	0.044	0.084	0.093
N	886	880	886	880

Table 14 reports the effect of the treatments by trust quartile, using ANCOVA estimations and interacting a dummy variable capturing the respondent's level of trust with each one of the treatment dummies. The dummy variable "Least trusting" captures whether a farmer is below the 25th trust index quartile (i.e., calculated using the trust index used by Fehr (2009)), taking the value of 1 if yes and 0 otherwise. Standard errors are presented in parentheses below the coefficients. The statistical significance reported has the standard interpretation and corresponds to the statistically significant effects of the treatments in inducing one step changes in the likelihood of adopting the recommended practices (columns (1)-(4)). All the regressions use clustered standard errors at the cooperative level. * p<0.1, ** p<0.05, *** p<0.01.

Table 15A. Cost of different ICTs per targeted farmer and farmer adopting the practice

	Radio		**IVR**		**App**		**Extension Training**	
Number of participants	**USD/targeted farmer**	**USD/farmer adopting**	**USD/targeted farmer**	**USD/farmer adopting**	**USD/targeted farmer**	**USD/farmer adopting**	**USD/targeted farmer**	**USD/farmer adopting**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
886	143	5,975	246	12,304	203	3,447	672	6,588
5,000	25	1,059	44	2,180	36	611	672	6,588
10,000	13	529	22	1,090	18	305	672	6,588
50,000	2.5	106	4.4	218	3.6	61	672	6,588
100,000	1.3	53	2.2	109	1.8	31	672	6,588
1,000,000	0.13	5.3	0.22	11	0.18	3.1	672	6,588

To estimate the cost per farmer of adopting the technology (columns (2),(4), (6), and (8), we use the adoption rates found in this study in table 4, column (6) for the app treatment (5.9%), table 5 column (6) for the radio treatment (2.4%), table 6 column (6) for the training treatment (10.2%), and table 7 column (6) for the IVR treatment (2%).

Table 15B. Cost of different ICTs per female and male farmers adopting the practice

	Radio		**IVR**		**App**		**Extension Training**	
Number of participants	**USD/female farmer adopting**	**USD/male farmer adopting**	**USD/female farmer adopting**	**USD/male farmer adopting**	**USD/female farmer adopting**	**USD/male farmer adopting**	**USD/female farmer adopting**	**USD/male farmer adopting**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
886	1,938	n/a	22,370	4,921	5,811	2,187	4,098	8,400
5,000	343	n/a	3,964	872	1,030	388	4,098	8,400
10,000	172	n/a	1,982	436	515	194	4,098	8,400
50,000	34	n/a	396	87	103	39	4,098	8,400
100,000	17	n/a	198	44	51	19	4,098	8,400
1,000,000	2	n/a	20	4	5	2	4,098	8,400

To estimate the cost per female and male farmer adopting the technology, we use the adoption rates found in the bottom of Table 10, column 6. For the app treatment the female (male) adoption rates are 3.5% (9.3%), for the radio treatment 7.4% (null), for the IVR treatment 1.1% (5%), and for the training treatment 16.4% (8%).