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Impacts of Personalized Picture-based Crop Advisories

Experimental Evidence from India and Kenya

Francisco Ceballos

Aditi Chugh

Berber Kramer

Markets, Trade, and Institutions Unit

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AUTHORS

Francisco Ceballos (f.ceballos@cgiar.org) is a Research Fellow in the Markets, Trade, and Institutions (MTI) Unit of the International Food Policy Research Institute (IFPRI), Washington, DC.

Aditi Chugh (a.chugh@cgiar.org) is a Research Analyst with IFPRI's MTI Unit, Washington, DC.

Berber Kramer (b.kramer@cgiar.org) is a Senior Research Fellow with IFPRI's MTI Unit, Nairobi, Kenya.

Notices

Abstract

The rise of artificial intelligence (AI) has heightened interest in digital models to strengthen agricultural extension. Such tools could help provide personalized advisories tailored to a farmer's unique conditions at scale and at a low cost. This study evaluates the fundamental assumption that personalized crop advisories are more effective than generic ones. By means of a large-scale randomized controlled trial (RCT), we assess the impact of personalized picture-based advisories on farmers' perceptions, knowledge and adoption of recommended inputs and practices, and other downstream outcomes. We find that personalizing advisories does not significantly improve agricultural outcomes compared to generic ones. While farmers who engage relatively more with advisories (i.e., those who receive and read a substantial number of messages based on self-reports) tend to achieve better outcomes, this is irrespective of whether the advisories they receive are tailored to their specific situation or not. We conclude that investments in digital extension tools should aim to enhance engagement with advisories rather than focusing solely on personalization.

Keywords: Digital, extension, advisories, agriculture

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1. Introduction

Enhancing agricultural productivity and fostering sustainable agricultural development is a critical challenge for developing nations, but progress is usually hindered by disparities between nations, crops, and regions, as well as climate change threats (Naresh et al. 2017; IPCC 2022). While adhering to good agricultural practices and adopting recommended agricultural technologies have the potential to alleviate poverty and improve development outcomes, uptake has been typically slow and uneven (Sunding and Zilberman 2001; Steensland 2021). Previous studies have identified limited access to finance, lack of insurance against risks, and insufficient information as key barriers hindering the adoption of technologies that could enhance yields and resilience (Feder, Just, and Zilberman 1985; Foster and Rosenzweig 1995, 2010; Jack 2013; Suri and Udry 2022).

In this context, extension services play a crucial role in improving smallholder farmers' productivity and incomes by promoting sustainable agricultural practices and facilitating climate adaptation (de Janvry and Sadoulet 2020, World Bank 2007). However, the effectiveness and reach of traditional, in-person extension services has been limited (Birkhaeuser et al. 1991; Ogundari 2022; Taye 2013). In this context, the advent of mobile communication technologies and, more recently, artificial intelligence (AI), has geared practitioners towards the promises behind the digitalization of agricultural extension. As a result, many countries increasingly rely on mobile phones to deepen the reach of agricultural extension at a lower cost. Such use of information and communication technologies (ICTs) and digital technologies can potentially reduce the costs of extension services and facilitate better communication between farmers and extension agents, as well as among farmers themselves, enabling the dissemination of more accurate and interactive advisories tailored to a farmer's needs.

The evidence of the impact of digital extension on technology adoption and yields is however mixed, with some studies showing positive effects (Aker et al. 2016; Fabregas et al. 2019), and others reporting more limited benefits (Nakasone et al. 2014; Baumueller 2015). In addition, the use of mobile phones has mainly allowed for one-way extension—where extension providers send large numbers of farmers text messages about recommended agricultural practices based on general information on weather, planting dates, and crops grown in a broad area—with limited opportunities for farmers to receive personalized feedback based on their unique conditions, as those commonly provided during in-person visits from extension agents.

This study analyzes the potential for personalizing ICT-based extension services by using smartphone technology to mimic farmers' interaction with extension agents but using a less time-intensive and lower cost approach compared to in-person visits. In particular, it evaluates a novel personalized remote advisory service that tailors recommendations based on experts reviewing smartphone images of a farmer's crops. Farmers enrolled in so-called Picture-Based Advisories (PBA) can send in smartphone pictures of their crops throughout the growing season and communicate a concern they may have about their crop's growth. Crop agronomists review incoming pictures—together with any farmer-submitted questions or concerns—and provide personalized advice remotely within a short time frame, allowing for very high levels of tailoring.

Such a system could in principle allow agronomists to monitor crop growth, identify potential issues of concern locally or across broad areas, and recommend preventive or curative measures to avoid impending crop damage or to minimize damage *ex post*. Such advice can be personalized to the farmer's field and to specific issues encountered, at a larger scale than can be achieved through traditional in-person extension systems. At the same time, there is a cost to this type of personalization, both in terms of human and financial resources required to implement it and in terms of the necessary shift to digital platforms for delivering the advisories, which can be detrimental to the engagement and understanding of less digitally-literate farmers and those with limited smartphone access.

To evaluate the effects of this innovation, we implemented a cluster randomized control trial in Haryana, a state in northwest India, and seven counties across different regions of Kenya. We randomly assigned half of our 257 study villages to a treatment arm, where farmers were offered free picture-based advisories from well-known local agricultural research centers.

The remaining study villages, where farmers received generic advisories, served as our control group. The study targeted a sample of 2,000 wheat, rice, and tomato farmers in India and 1,200 maize, sorghum, and legume-producing smallholder farmers in Kenya, which were provided with advisories over three agricultural seasons.

We find very limited effects of personalized advisories on a range of outcomes, regardless of how many advisories a farmer received, and of whether those advisories were provided in response to observing specific issues in a farmer's field. First and foremost, farmers in the treatment group did not perceive the picture-based advisories they received to be more relevant or personalized compared to farmers in the control group, who received generic advisories. Unsurprisingly, then, we see no downstream impacts on knowledge around topics that were covered through the advisories, adoption of recommended inputs and practices—except for modest reductions in fertilizer and pesticide use, and a small increase (decrease) in family (hired) labor—average yields, damage, profitability, or incomes.

To better understand why the advisories had no impacts, we use propensity score matching to analyze if this can be attributed to farmers not engaging with the advisories. Across both control and treatment arms, we find that farmers who received and read the advisories perceived the advisories more positively, and achieved better knowledge outcomes, than comparable farmers who did not receive or read the messages. However, even for this subsample of more engaged farmers, we observe no significant differences in outcomes between the groups receiving personalized and generic advice. Similarly, we test for differences in outcomes between farmers who self-reported perceiving the messages as being personalized and comparable farmers who did not, and find significant positive differences in terms of perception, knowledge, and adoption outcomes. These results indicate that when the advice received feels appropriate and relevant to their specific context, farmers are more likely to engage with it and apply it successfully.

In other words, the combination of our experimental findings with those from quasi-experimental methods suggests that personalization alone is not enough, and what is perhaps more important is farmers' engagement with advisories. Based on this evidence, we conclude that the small observed benefits of personalization are not worth their extra cost if not supplemented with additional measures to increase farmers' ability to access, read, understand, and overall engage with the advisories.

Our paper relates to the existing literature on agricultural extension in different ways. First, we describe the real-world implementation and assess the impacts of a new, two-way model for digital or phone-based extension. As mentioned above, the literature on digital extension has mostly focused on one-way models, that is, experts sending fairly general advice over digital media, such as SMS, interactive voice response (IVR), or videos (see, for instance, Cole and Fernando 2021; Fabregas et al. 2022, 2024; Fu and Akter 2016; Gandhi et al. 2007; Van Campenhout 2021). Second, and somewhat related, this model allows for higher levels of tailoring of the advice, only akin to the type of advice that traditional, in-person extension agents can provide (Birkhaeuser et al. 1991; Ogundari 2022; Taye 2013), but at a considerably lower cost and broader reach. Third, we provide evidence on the importance of factors usually overlooked in the literature, in particular in terms of how farmer engagement with digital advisories mediates potential impacts (Abdulai et al. 2023a, 2023b; Adereti et al. 2024). All three of these are crucial to inform current debates around the use of AI to improve the quality and accessibility of extension services, still a nascent literature (Tzachor et al. 2023).

The remainder of the paper is structured as follows. In the next section, we provide contextual background, a discussion of the overall study design and intervention, the hypotheses that we aim to test, and methods used. Section 3 describes study implementation, including a full description of the system of advisories, and the different data sourced used in the analyses. Section 4 presents the main results regarding the impacts of personalized advisories, using experimental variation in whether a farmer received personalized or generic advisories, while Section 5 provides quasi-experimental evidence, using propensity score matching to investigate whether farmers who engage more with the advisories achieve better outcomes. In the final section, we discuss the implications of our findings and provide some concluding remarks.

2. Context and Methods

2.1 Study Context and Intervention

The study was implemented in two countries, Kenya and India, to enhance external validity of study findings. We worked with agricultural research partners from both countries to provide PBA in five districts of the state of Haryana in India (Ambala, Karnal, Kurukshetra, Panipat, and Yamunanagar), and in seven counties in three regions of Kenya (Bungoma and Busia in Western Kenya, Embu, Meru and Tharaka-Nithi in the upper Eastern part of Kenya, and Machakos and Makueni in the lower Eastern part of the country).

Haryana, the fourth largest wheat producer in India, benefits from high irrigation, fertilizer use, and mechanization, leading to higher agricultural incomes and larger landholdings compared to other states. However, recent stagnation in yield growth and challenges like depleted water tables and poor soil fertility (Ministry of Agriculture and Farmer's Welfare, 2016) have emerged, while the increasing prevalence of mobile phones and internet access in rural areas has created an opportunity to test the effectiveness of remote, personalized agricultural advisories, potentially scaling this service both within India and globally (ICEA 2020). On the other hand, Haryana faces significant inequities related to caste, landholdings, and gender, with upper-caste farmers owning larger landholdings and benefiting from better access to resources, while lower-caste farmers face higher production risks and less government support (Drèze and Sen 2013; Goli et al. 2021). Gender inequities, including women's disempowerment and violence, are prevalent, with traditional norms limiting women's involvement in agriculture and decision-making, which could be further worsened by crop income losses (Misra et al. 2020; Farnworth et al. 2020). It is thus important to understand the representativeness of our sample and assess heterogeneity in impacts in the context of our study.

In Kenya, the study targeted seven counties in the Western, upper Eastern and lower Eastern parts of the country. The economy in each of these regions relies heavily on the agricultural sector. Agriculture contributes 22.4 percent of the country's GDP, with most producers being smallholder farmers (KNBS, 2022). This leaves both the economy and the farmers who make up the economic base facing significant risk. Shock events in the recent past underscore this truth. Notably, Kenya experienced significant drought events in 2008-2011 (MOALF, 2021), 2016-2017 (Uhe et al., 2018), and 2020-2022 (FAO, 2021). Such shocks have immediate and lasting effects on farmer well-being (Rosenzweig and Binswanger, 1993; Carter, 1997; Morduch, 1995; Hoddinott, 2006; Janzen and Carter, 2019; Malacarne and Paul, 2022), underscoring the pressing need to strengthen the resilience of smallholder farmers. To manage such risks, agricultural insurance options like conventional and index-based contracts are available, but uptake remains very low, with less than 1% of farmers insured as of 2020 (KNBS, 2022).

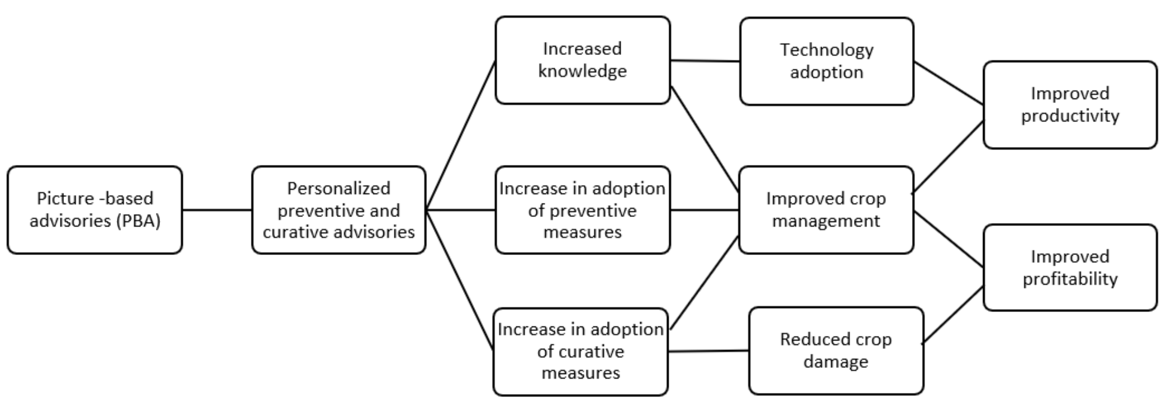
We evaluate Picture-Based Advisories (PBA), a personalized remote advisory service that tailors recommendations based on smartphone images of a farmer's crops.[1] Farmers with this type of low-cost, interactive advisory service can send in smartphone pictures of their fields throughout the growing season and submit close-up images to communicate a concern they may have about their crop's growth. Crop agronomists review incoming pictures, together with any farmer-submitted questions or concerns, through a dedicated web platform, based on which they provide personalized text- or audio-based advice within a short time frame (usually under 24-48hs), allowing for unprecedented levels of tailoring and timeliness of remote advisories. This interaction is enabled by a dedicated smartphone app that includes functionality to take overview and close-up pictures (and automatically upload them to the cloud), submit accompanying text- or audio-based questions, and receive text- or audio-based advice from experts, with the possibility of including pictures or links to other sources for additional information.

As an advisory system, PBA has several potential advantages over generic advisories (see Figure 1 for a theory of change). Based on regular pictures of a farmer's field, together with

[1] The intervention was integrated into ongoing randomized impact evaluations of Picture Based Insurance (PBI), which uses smartphone pictures to detect crop damage and settle insurance claims. Initially launched in Haryana, India, during the 2016/17 wheat Rabi season, PBI expanded in subsequent years to other areas of India, as well as parts of Ethiopia and Kenya.

weather reports and pictures from other farmers in the area, agronomists have more information available to them and can monitor crop growth, identify potential issues of concern, and detect damage from a wide variety of causes. As a result, they can recommend both preventive and curative measures, personalized to the farmer's field and specific issues encountered, at a larger scale than can be achieved through a regular in-person extension system.[2] By increasing attention paid to and understanding of advisory messages, this can enhance farmer knowledge around crop management. Moreover, personalization could also foster farmer ownership, encouraging adoption of both preventive and curative practices. These, in turn, would result in improved technology adoption, crop management, and reduced crop damage. Ultimately, technology adoption and improved crop management can improve crop productivity and, together with reduced crop damage, improve profitability.

Figure 1. Theory of change



Source: authors.

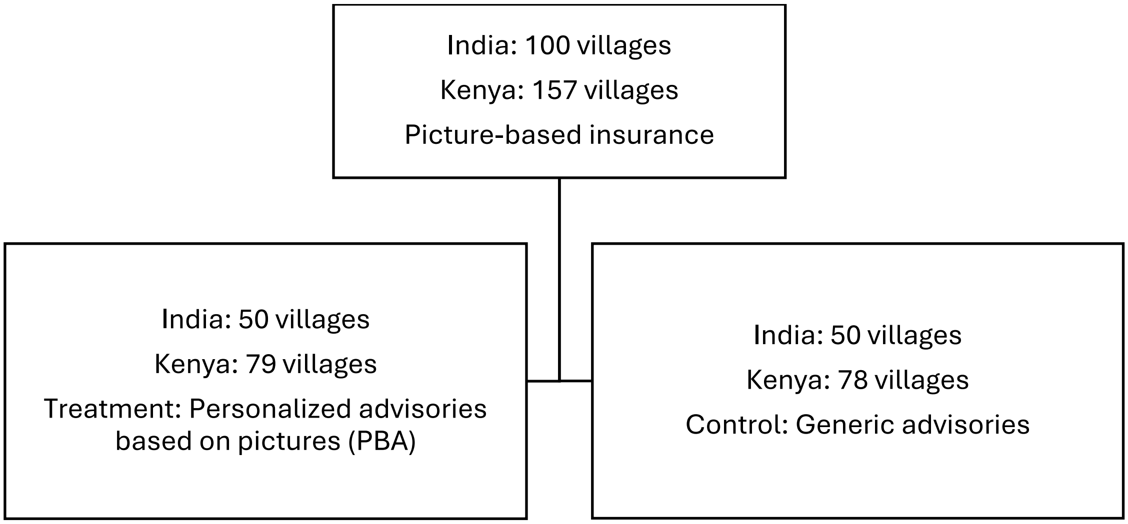
[2] We refer to messages as preventive when they communicate general advice around farming of a given crop. Curative messages, on the other hand, address a specific issue seen in the pictures sent by the farmer and aim to help the farmer diagnose, minimize, or cure any potential sources of damage or implement a currently missing practice to maximize the crop's yield. By definition, curative messages were only sent in the personalized advisories treatment arm.

2.2 Experimental Design

To test the above hypotheses, we implemented a two-country cluster randomized control trial in 100 villages in the state of Haryana, India, and in 157 villages in seven counties from different regions in Kenya, with the objective of evaluating the effect of offering farmers image-based, tailored advisories on knowledge, technology adoption, and farming outcomes. In India, the impact evaluation focused on a sample of 2,000 wheat, rice, and tomato farmers, while in Kenya it targeted 1,256 smallholder farmers producing maize, sorghum, and beans. The project comprised three agricultural seasons: the Kharif 2022 (May–November), the Rabi 2022-23 (October–March), and the Kharif 2023 seasons in India, and the Long Rains 2022 (March–August), Short Rains 2022-23 (September–February), and Long Rains 2023 seasons in Kenya. A key implementation difference between India and Kenya is that project activities in Kenya were centralized by a single individual in each study village, a champion farmer, who was contracted by ACRE Africa (our local implementation partner), and trained at the beginning of each season to liaise with farmers.

In a randomly selected 50 percent of these villages, farmers were offered a free PBA service, whereby recommendations were sent to farmers based on smartphone pictures of their crops. In the other 50 percent of study villages, farmers were offered an advisory service that provided more generic information, not tailored to a farmer's personal situation (see Figure 2). To minimize the risk of spillovers and jealousy, assignment into the PBA treatment versus the control group with generic advisories was randomized at the village level. As a result, comparing outcomes between the control and treatment arm allows us to isolate the marginal effect of personalized advisories on our outcome and impact variables.

Figure 2. Experimental Design



Source: authors.

2.3 Empirical Strategy

We pursue four different approaches to estimate the effects of PBA on farmer knowledge, technology adoption, and agricultural outcomes. First, we estimate the intent-to-treat (ITT) effect of offering personalized advisories. To that end, we pool data across crops from both countries and estimate the following equation for outcome Y of household i and crop c in village v:

$$Y_{ivc} = \alpha + \beta_1 T_v + \gamma_1 N_v + \gamma_2 C_{ivc} + \delta X_{iv} + \varepsilon_{ivc} \quad (1)$$

where T_v is a dummy variable indicating whether household i resides in a treatment village where we offered the personalized advisory service; N_{iv} is a variable indicating the country where that household is located (1 if Kenya, 0 if India), and C_{ivc} is a vector of crop indicators, using as the omitted category the modal crop in both countries (paddy in India, maize in Kenya); X_{iv} is a vector of farmer- and village-level controls measured at baseline (including farmer gender and age, household size, whether a farmer is married, belongs to a scheduled caste, tribe, or other backward caste, whether the farmer has completed at least primary education, whether the household owns land, the number of acres owned, whether agriculture is the main source of income, and whether at least someone in the farmer's household owns or has access to a smartphone), and ε_{ivc} is the residual, which we cluster at the village level. In addition, we include an indicator variable that captures whether the farmer is in a village in India that was added to the sample at the start of this project (to distinguish from older villages where other project interventions had been taking place for a few years), a set of indicator variables capturing the treatment status of a village in previous interventions in Kenya, dummies by county (Kenya) and block (India), over which the treatment assignment was stratified, and indicator variables identifying the enumerator that interviewed the farmer at baseline.

We extend the above equation to analyze heterogeneity by country,

$$Y_{ivc} = \alpha + \beta_1 T_v + \beta_2 T_v \times N_{iv} + \gamma_1 N_{iv} + \gamma_2 C_{ivc} + \delta X_{iv} + \varepsilon_{ivc} \quad (2)$$

and to assess heterogeneity by treatment intensity, including a continuous indicator of the number of advisories that a farmer received for a given crop,

$$Y_{ivc} = \alpha + \beta_1 T_v + \beta_2 A_{ivc} + \beta_3 T_v \times A_{ivc} + \gamma_1 N_{iv} + \gamma_2 C_{ivc} + \delta X_{iv0} + \varepsilon_{ivc} \quad (3)$$

where A_{ivc} indicates the inverse hyperbolic sine of the number of advisories received by individual i for crop c, so that $\widehat{\beta_1}$, is estimated as the treatment effect for farmers having received zero advisory messages, and $\widehat{\beta_3}$ identifies any additional effect stemming from the number of advisories received.

Finally, we depart from the framework above to analyze treatment heterogeneity by advisory topic. To do this, we explore changes across multiple outcomes per farmer relating to input use, willingness to adopt and actual adoption of recommended agricultural practices and technologies, and adoption of recommended crop varieties associated with receiving advisories about those topics. In this pooled data structure, where every observation represents a topic-specific activity on which advisories may have been received by individual i for crop c, we estimate a model with fixed effects at the household-crop level (η_{ivc}) and including topic dummies (θ_{ivc}), with A_{ivct} capturing the number of advisory messages that the farmer received for subject t, and Y_{ivct} corresponding to outcome variables related to subject or topic t, as follows,

$$Y_{ivct} = \alpha + \beta_1 A_{ivct} + \beta_2 T_v \times A_{ivct} + \eta_{ivc} + \theta_{ivc} + \varepsilon_{ivc} \quad (4)$$

In our analyses, we focus on the same overall set of outcomes, which we divide into 6 distinct groups. The first group relates to participation in the project interventions: whether a farmer received any advisory messages at least once and the number of advisories received, as captured by administrative data, in addition to whether a farmer self-reported having received at least one advisory and whether they thought that advisories were tailored to their crop's needs, as captured during the endline survey.

The second group of outcomes explores farmers' perceptions of the advisory service at endline, including whether advisories helped them to learn new information, minimize risks, save time, lower costs, improve the quality of the crop, and improve yields, and a total score for these six variables.

A third group of outcomes focuses on farmers' knowledge and adoption of recommended practices and technologies, and of improved practices and technologies more broadly. To measure knowledge, we assess the number of correct answers in a knowledge test comprised of six questions regarding topics covered in the advisory service. In addition, we include the number of crop-specific practices (out of a small set of practices directly related to the advisories sent) for which farmers say they know how to implement them, and the number of these practices implemented at endline. The design of both the knowledge test and the set of advisories-related practices was done in collaboration with our local advisory partners (BISA in India and KALRO in Kenya), given their familiarity with the topics on which farmers had been receiving advice. Finally, we capture whether a farmer has both used or is planning to use a crop variety recommended through the advisory.

Next, we focus on inputs used in farming, on which we have data disaggregated by crop. One group of outcomes relates to the amount of labor used, distinguishing between hired male and female labor, family male and female labor, own labor from the main farmer, and the number of times that the main farmer visited the main plot during the last season. Another group relates to the cost of inputs applied during the last season, including fertilizers, pesticides/insecticides, fungicides, herbicides, and irrigation.

Finally, the sixth group considers general farming outcomes from the last season, including the area under cultivation with study crops, crop yields, and the extent to which farmers self-reported experiencing crop damage (both as a percentage of damage and as a binary variable capturing whether a given farmer reported having damage above 20%, the average self-reported damage level across the full sample).

3. Implementation and data collection

In India, the program was implemented over three agricultural seasons spanning from August 2022 to December 2023: Kharif 2022, Rabi 2022-23, and Kharif 2023. At the beginning of each season, staff from BISA visited sampled farmers in-person to offer them the opportunity to enroll in advisories (either generic or personalized depending on the village) for their paddy, wheat, or tomato crops. Interested farmers had to register in a specialized smartphone application called KisanCam developed specifically for the program. Farmers were then instructed to take pictures of their fields throughout the season, including additional close-up pictures in case they had any questions about the growth of their crop or if they wanted to document any issues. Throughout the season, a dedicated small team of BISA staff monitored incoming pictures and followed up with farmers not sending pictures or with those who had a technical problem with the app.

In Kenya, the program was also implemented over three agricultural seasons: Long Rains 2022, Short Rains 2022-23, and Long Rains 2023. A key implementation difference with India, however, is that project activities in Kenya were centralized by a single individual in each study village, a champion farmer, trained at the beginning of each season to liaise with farmers. At the beginning of each season champion farmers communicated project information to farmers and enrolled interested farmers in the intervention. Similarly to India, participating farmers had their sites enrolled in the champion farmer's app (named SeeItGrow in Kenya), where the champion farmer took regular pictures of each farmer's fields throughout the season and received advisory messages on behalf of them. In addition, farmers received the same advisory messages on their own phones via SMS. A small, dedicated team of KALRO staff monitored incoming pictures and followed up with champion farmers not sending pictures or with those who had a technical problem with the app.

Table 1 summarizes the number of farmers participating in the different project activities by agricultural season in both India and Kenya. In India, we first invited 20 randomly selected farmers from every village to enroll in advisories (either generic or personalized, depending on their village's treatment assignment), but due to low enrolment, we later added an additional set of randomly selected farmers per village. All in all, a total of 3,385 farmers across all 100 villages were invited to participate in the program each season, comprised of 1,711 farmers from the 50 PBA treatment villages and 1,674 farmers from the 50 control villages. In Kenya, 20 farmers per village were invited to participate. The next set of columns displays the number of farmers who enrolled in the advisories. In India, around 10% of invited farmers enrolled during the first season (Kharif 2022), similar across the generic and personalized treatment arms. The fraction of farmers participating in advisories increased over time, however, with an overall enrollment rate of 13% for Rabi 2022-23 tomato, 24% for Rabi 2022-23 wheat, and 27% for Kharif 2023 paddy, still similarly distributed across treatment arms as during the first season. Enrollment in advisories was considerably higher in Kenya, with rates between 70 and 80% for maize, though substantially lower across the three other crops of interest (sorghum, green grams, and beans). Higher enrolment rates are arguably due to the champion farmer model, where individual farmers did not have to enroll their own site in SeeItGrow, but rather only accept the champion farmer doing so on their behalf. In terms of the difference between maize and other crops, the app only allowed for enrolment of one single crop for receiving advisories each season, and maize is usually the crop regarded as most important by Kenyan farmers.[3]

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[3] Because of this stark difference in enrolment rates in advisories between maize and the other crops, we omit sorghum, beans, and green grams as standalone crops from the analysis moving forward and include beans only as part of the maize-beans intercropping tandem, which is quite common in our sample.

Developing and setting up a system of advisories in both settings constituted an important portion of implementation activities. The initial goal was for all farmers to receive a single advisory message every 14 days, regardless of their treatment assignment, to ensure equal treatment intensity across treatment groups. We therefore sent farmers in the control arm a pre-determined, generic advisory message each fortnight, based on recommended practices from regular crop calendars given self-reported sowing dates. Specifically, every 14 days from sowing, farmers received a generic advisory indicating common crop management practices to be implemented around that phase of crop growth (e.g., applying irrigation, applying fertilizer in the appropriate quantities, preventing pests and diseases, and so on). Similarly, those in treatment villages with personalized advisories received a single advisory issued by a local agronomic expert every 14 days. The advice was based on any issues observed across all pictures received from that farmer in the previous 14 days and informed by an expert's knowledge of the crop and related crop calendars, typical management practices, recent or expected weather, and current issues being experienced by other farmers in the area. For farmers who did not submit pictures in the previous 14 days, experts drafted an advisory informed by pictures of neighboring farmers' fields. Finally, in those cases where no images from neighboring farmers were available, a standard advisory was sent by the expert based on general patterns they observed in the region, current weather forecasts, or information on upcoming practices according to the crop calendar.

Table 1. Number of farmers participating in implementation activities

Country	Season	Crop	A. Number of farmers invited to participate		B. Number of farmers enrolled in advisories	
			Generic	Personalized	Generic	Personalized
India	Kharif 2022	Paddy	1,674	1,711	168	160
	Rabi 2022/23	Tomato	1,674	1,711	221	233
		Wheat	1,674	1,711	447	382
	Kharif 2023	Paddy	1,674	1,711	479	436
Kenya	Long Rains 2022	Maize	892	887	653	646
		Sorghum			16	18
		Green grams			64	30
		Beans			17	41
	Short Rains 2022/23	Maize	1,557	1,545	1,292	1,200
		Sorghum			68	44
		Green grams			43	86
		Beans			11	15
	Long Rains 2023	Maize	1,557	1,565	1,160	1,073
		Sorghum			21	30
		Green grams			108	132
		Beans			96	119

The back-end website (linked to farmers' smartphone app) allowed agricultural experts to see and approve incoming pictures, monitor the number of farmers needing advice in an advisory dashboard, issue personalized advice in an efficient manner (relying on editable re-usable templates or the ability to create new templates or completely new messages from scratch), and answer farmer queries through a non-real-time chat function. Experts in both settings issued personalized advisories based on visible cues and developed a pre-determined list of generic advisories for each crop of interest (which, as mentioned above, were automatically programmed on the online servers to be sent at an interval of 14 days since the sowing date indicated by each farmer when enrolling a site at the beginning of the season). All advisories were written and sent by experts directly from the website. Once drafted and sent, an algorithm pushed each advisory through two different channels: (1) an incoming advisory tab within the app (received by farmers themselves in India and by champion farmers in Kenya), and (2) an SMS sent directly to the farmer.

Table 2 shows the number of advisory messages sent during the project, by crop and season, distinguishing between generic messages sent to farmers in control villages and personalized advisories sent to farmers in treatment villages. The first row in each panel shows the total number of messages sent, while the following rows do so by type of advisory—whether messages were of a preventive or curative nature, or if they carried no specific advice. Overall, almost 40,000 advisory messages were sent in India and more than 50,000 in Kenya, with most advisories corresponding to the most common cereal crops in each setting: wheat and paddy in India and maize in Kenya. The number of advisories sent per farmer in a given crop and season ranges from 3 to 13, with an average of 6.3, and no systematic differences across crops, settings, or over time.

In terms of the type of messages sent, we classify messages into three main categories: no advice (a message with no specific advice, such as "your crop is doing well"), preventive (a message containing general preventive advice but with no specific information tailored to the farmer's situation), and curative (a situation where an expert identified a specific issue in the farmer's crop and sent a message containing instructions on how to minimize or resolve that issue). Overall, implementation fidelity was high, with all generic messages being of a preventive nature, and a fraction of personalized advisories being of a curative nature, providing expert advice for specific issues observed in the pictures. However, a large fraction of personalized messages did not include any advice at all, usually acknowledging receipt of the pictures and informing the farmer that the crop looked well at the time. In addition, a substantial number of messages in the personalized treatment arm were of a preventive nature, and thus closer to generic advisories. In India, no curative messages were sent in the personalized treatment arm in Kharif 2022 and the proportion of curative messages in the personalized treatment arm was very small (between 2 and 7% of the total messages sent); unlike Kenya, where curative messages usually represented more than half of those sent, suggestive that implementation quality was generally lower in India.

We rely on two main sources of data collection in both settings. At the onset of the project, we collected baseline survey data for all 20 targeted farmers per village in India, and for a randomly selected 12 farmers of the 20 targeted farmers per village in Kenya. Our main outcomes for the analyses are derived from an endline survey conducted in November and December 2023 with the full baseline sample in India, and a subset of 8 farmers per village in Kenya. The decision to reduce the number of farmers per village in the Kenya endline survey was guided by power calculations, showing that due to an increase in the number of clusters from 60 to 157, the study was still sufficiently powered by surveying only 8 farmers per sampled village. We also use administrative data and advisory data collected throughout the implementation period in both countries in the analyses. These data include, for each personalized advisory, expert-reported classifications for the general topic of the advice, the problem identified in the pictures, the specific practices/technologies being recommended, and whether the advice was of a preventive or curative nature. These data were collected by means of a short questionnaire that experts filled out after sending each advisory. Similar data were collected for generic advisories when the messages were developed.

Table 2. Advisory messages sent by category

Panel A. India

	Kharif 2022		Rabi 2022/23				Kharif 2023	
	Paddy		Wheat		Tomato		Paddy	
	Generic	Personalized	Generic	Personalized	Generic	Personalized	Generic	Personalized
Total	6,030	5,985	5,560	9,400	987	2,131	3,611	4,643
No advice	-	-	-	6,322	-	1,939	-	1,871
Preventive	6,030	5,985	5,560	2,946	989	42	3,612	2,656
Curative	-	-	-	132	-	150	-	116

Panel B. Kenya

	Long Rains 2022				Short Rains 2022-23				Long Rains 2023			
	Maize		Beans		Maize		Beans		Maize		Beans	
	Gene-ric	Perso-nalized	Gene-ric	Perso-nalized	Gene-ric	Perso-nalized	Gene-ric	Perso-nalized	Gene-ric	Perso-nalized	Gene-ric	Perso-nalized
Total	6,045	2,984	265	172	14,477	10,731	117	129	5,167	4,755	419	460
No advice	-	125	-	8	-	3,536	-	25	-	1,308	-	82
Preventive	6,045	271	265	1	14,477	1,294	117	15	5,167	798	419	82
Curative	-	2,588	-	163	-	5,901	-	89	-	2,649	-	296

Table 3 checks for balance between treatment arms by reporting the results of mean tests across both arms in both settings for a set of key household and main farmer characteristics at baseline. Overall, randomization seems to have produced fairly balanced treatment and control groups, with almost no statistically significant differences between the generic and personalized advisories treatment groups. The only exception is in Kenya, where farmers in the treatment arm are five percentage points more likely to be married than control group farmers ($p < 0.05$).

Table 3. Balance tables across generic/personalized treatment arms

	Control (generic advisories)	Treatment (personalized advisories)	p-val diff. col. 1-2	No. of observations
	(1)	(2)	(3)	(4)
Panel A. India				
Main farmer is female	0.001	0.003	0.300	1,924
	(0.032)	(0.056)		
Main farmer's age	46.27	47.33	0.158	1,924
	(12.59)	(12.13)		
Main farmer is married	0.954	0.948	0.604	1,924
	(0.210)	(0.222)		
Main farmer completed primary education	0.939	0.947	0.555	1,924
	(0.240)	(0.224)		
Main farmer completed secondary education	0.742	0.758	0.567	1,924
	(0.438)	(0.428)		
Religion: Hindu	0.933	0.936	0.941	1,924
	(0.249)	(0.245)		
Backward caste	0.491	0.585	0.145	1,924
	(0.500)	(0.493)		
Agriculture is the household's only source of income	0.781	0.791	0.741	1,924
	(0.414)	(0.407)		
Household owns or has access to a smartphone	0.947	0.951	0.791	1,924
	(0.225)	(0.215)		
Panel B. Kenya				
Main farmer is female	0.665	0.641	0.399	1,414
	(0.472)	(0.480)		
Main farmer's age	48.47	49.22	0.424	1,414
	(13.80)	(13.38)		
Main farmer is married	0.760	0.810	0.024	1,414
	(0.428)	(0.392)		
Main farmer completed primary education	0.709	0.741	0.601	1,414
	(0.455)	(0.438)		
Main farmer completed secondary education	0.290	0.322	0.186	1,414
	(0.454)	(0.468)		
Household size	6.437	6.707	0.234	1,414
	(2.775)	(2.974)		
Religion: Protestant	0.165	0.115	0.218	1,414
	(0.372)	(0.319)		
Total cultivated lands (in acres)	1.991	2.221	0.369	1,414
	(1.509)	(2.120)		
Agriculture is the household's main source of income	0.799	0.765	0.199	1,414
	(0.401)	(0.424)		

4. Results

This section summarizes the main results from the impact evaluation. As discussed above, in the case of India we focus on Kharif 2023 paddy and Rabi 2022-23 wheat and tomato, while in Kenya on Maize and intercropped plots with Maize-Beans in the Short Rains 2022-23 and in the Long Rains 2023 seasons (though during the endline survey in Kenya farmers were asked about the latest season where they grew a crop, so most observations correspond to the Long Rains 2023 season). We discuss estimates for the full sample as well as disaggregated ones for the two countries, to assess the external validity of our results and uncover location-specific mechanisms.

We first present estimates of Equations (1) and (2). These are intent-to-treat (ITT) estimates that compare outcomes for all farmers offered personalized versus generic advisories. Since, depending on the setting and crop, implementation reached a relatively small proportion of farmers, we also present average treatment effects among farmers who received at least one advisory message in either treatment arm, which we refer to as treatment-on-the-treated estimates (ToT). Appendix Tables A.1 through A.6 use Equation (3) to investigate whether treatment effects vary by treatment intensity, for which we interact treatment with either the number of total advisory messages received by each farmer or the number of curative advisories, which best capture the personalized spirit of PBA. In these specifications, the coefficient on PBA treatment represents the treatment effect for farmers who did not receive any advisories (or specifically, curative advisories in the case of Panel B). Because we use an inverse hyperbolic sine transformation for the number of advisories, the coefficient on the interaction between treatment and number of advisories (or curative advisories) sent can be interpreted as the treatment effect when the number of advisories sent to farmers increases by one percent.

Table 4 shows ITT estimates on program participation outcomes in aggregate (Panel A) and by country (Panel B), with panels C and D presenting the ToT estimates, that is, treatment effects among those farmers who received at least one advisory message (either generic or personalized). Overall, farmers in the treatment arm are 5 percentage points less likely to have received advisories based on administrative data, but we see no differences between treatment and control in terms of the number of advisories received, in farmers reporting having received at least one advisory, or in farmers believing that the advisories were tailored to their specific situation. Although the ToT estimates (panels C and D) show a positive and statistically significant increase in the number of advisories received in the treatment arm (based on administrative data), we find no effects for the other participation variables. When exploring heterogeneity by treatment intensity (Appendix Table A.1), farmers who received a larger number of advisories are relatively more likely to report having received at least one advisory, and to find the advisories tailored to their needs; though this pattern is present in both the personalized and the generic messages treatment arms.

Table 5 focuses on outcomes related to farmers' perceptions around the advisories. Overall, we see little positive effects from being in the treatment arm on farmers' beliefs on whether the advisories helped them learn new information, improve yields, or economize on inputs. In fact, estimates of treatment effects are mostly negative and, in some cases, statistically significant, and this holds true for both settings and across both ITT estimates (Panels A and B) and ToT estimates (Panels C and D). On investigating further based on treatment intensity, we find no heterogeneity by number of overall advisories or number of curative advisories that a farmer received (Appendix Table A.2). Similarly, we find no effects on farmer knowledge and practice adoption across any of the specifications in Table 6 or in Appendix Table A.3. In summary, PBA did not shift farmers' perceptions of advisories or visibly improve their adoption or even knowledge of practices recommended through the advisory service, consistent with the results in Table 4 around farmers in the treatment arm not finding their advisories more personalized compared to those in the control group.

Tables 7 and 8 analyze self-reported labor and input use in target crops. Based on ITT estimates, we observe statistically significant decreases in hired male and female labor of around 3 and 2 hours per season, respectively (over a baseline of around 20 hours used for each type of labor in the control group), and an accompanying increase of 1.5 hours in labor from female family members (panel A). These patterns are mostly driven by Kenya but are also to some extent present in India (panel B). ToT estimates show stronger effects, including a statistically significant increase in both female and male family labor. This substitution from hired to family labor seems to be robust to the different specifications and could be explained in a few different ways. Receiving personalized advisories highlighting specific issues seen in the pictures may have prompted farmers to take the work in their own (or family members') hands, instead of relying on hired laborers. In addition, since pictures in India were normally taken by the household itself, this may have resulted in more frequent plot visits by family members (particularly among the youth, based on past qualitative work around PBI), conducting some of the regular weeding or input application work while there. In terms of other input application, however, we see no statistically significant effects for the aggregate sample in panel A, and only a small reduction in pesticide use in Kenya in panel B. Panels C and D show a slight decrease in the cost of irrigation, driven by Kenya, among those farmers that received personalized messages. Overall, it is difficult to interpret these coefficients, since more tailored advisories may prompt farmers to use either more or less inputs, depending on whether they were under- or over-applying these at baseline. The results from heterogeneity by treatment intensity (Appendix Tables A.4 and A.5) also suggest that the advisories are not necessarily driving the observed changes in input and labor use.

Table 4. Program participation – Overall and by country

PBA treatment arm coefficient for:	(1) Received at least one advisory (administrative data)	(2) Number of advisories received (IHS, administrative data)	(3) Received at least one advisory (self-reported)	(4) Advisories were tailored to crop's needs (self-reported)
Panel A. Aggregate effects - All interviewed farmers				
Full sample	-0.054**	-0.019	-0.002	0.003
	(0.024)	(0.064)	(0.019)	(0.018)
Panel B. Country-level effects - All interviewed farmers				
India	-0.058**	0.015	-0.005	-0.006
	(0.029)	(0.078)	(0.024)	(0.023)
Kenya	-0.040	-0.130	0.006	0.029
	(0.042)	(0.095)	(0.025)	(0.026)
Number of observations	5,501	5,501	5,501	5,501
Panel C. Aggregate effects - Farmers who received at least one advisory message				
Full sample	N/A	0.249***	-0.011	-0.016
	N/A	(0.026)	(0.021)	(0.020)
Panel D. Country-level effects - Farmers who received at least one advisory message				
India	N/A	0.432***	-0.013	-0.038
	N/A	(0.022)	(0.028)	(0.027)
Kenya	N/A	-0.054	-0.006	0.019
	N/A	(0.031)	(0.030)	(0.029)
Number of observations	N/A	2,708	2,708	2,708
Mean of outcome - Control group:				
Full sample	0.523	1.275	0.638	0.440
India	0.438	1.131	0.753	0.492
Kenya	0.803	1.750	0.258	0.269
Country dummy	Yes	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes

Table 5. Farmers' perceptions of advisories – Overall and by country

PBA treatment arm coefficient for:	**(1) Aggregate measure of perception (6 items)**	**(2) Advisories helped to: learn new information**	**(3) Advisories helped to: minimize risks**	**(4) Advisories helped to: save time**	**(5) Advisories helped to: lower costs**	**(6) Advisories helped to: improve the quality of the crop**	**(7) Advisories helped to: improve yields**
Panel A. Aggregate effects - All interviewed farmers							
Full sample	-0.150	-0.034*	0.004	-0.014	-0.029	-0.040	-0.036
	(0.100)	(0.017)	(0.032)	(0.027)	(0.018)	(0.030)	(0.029)
Panel B. Country-level effects - All interviewed farmers							
India	-0.115	-0.032*	0.014	-0.010	-0.021	-0.033	-0.034
	(0.107)	(0.019)	(0.035)	(0.029)	(0.019)	(0.033)	(0.032)
Kenya	-0.463**	-0.058	-0.092*	-0.055	-0.100**	-0.103**	-0.054
	(0.218)	(0.041)	(0.047)	(0.049)	(0.050)	(0.049)	(0.047)
Number of observations	3,548	3,548	3,548	3,548	3,548	3,548	3,548
Panel C. Aggregate effects - Farmers who received at least one advisory message							
Full sample	-0.238**	-0.049**	0.000	-0.002	-0.037	-0.088**	-0.063*
	(0.119)	(0.023)	(0.036)	(0.030)	(0.024)	(0.036)	(0.033)
Panel D. Country-level effects - Farmers who received at least one advisory message							
India	-0.180	-0.045*	0.024	0.011	-0.029	-0.079*	-0.062
	(0.132)	(0.025)	(0.042)	(0.035)	(0.026)	(0.041)	(0.038)
Kenya	-0.531	-0.069	-0.120	-0.070	-0.074	-0.135	-0.064
	(0.264)	(0.051)	(0.053)	(0.053)	(0.057)	(0.060)	(0.058)
Number of observations	1,688	1,688	1,688	1,688	1,688	1,688	1,688
Mean of outcome - Control group:							
Full sample	3.523	0.618	0.477	0.383	0.696	0.618	0.732
India	3.430	0.596	0.453	0.363	0.690	0.605	0.724
Kenya	4.417	0.833	0.708	0.571	0.750	0.738	0.815
Country dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. "***", "**", "*" indicate statistical significance at the 1, 5, and 10%, respectively.

Table 6. Knowledge and adoption – Overall and by country

PBA treatment arm coefficient for:	(1) Knowledge score (6 items)	(2) Number of practices farmer knows how to implement	(3) Number of practices farmer willing to adopt	(4) Number of recommended technologies used	(5) Used recommended crop variety last season	(6) Plans to use recommended crop variety next season
Panel A. Aggregate effects - All interviewed farmers						
Full sample	0.004	-0.008	0.011	-0.022	-0.014	-0.025
	(0.029)	(0.038)	(0.039)	(0.041)	(0.020)	(0.019)
Panel B. Country-level effects - All interviewed farmers						
India	0.007	-0.032	-0.019	-0.026	-0.020	-0.027
	(0.032)	(0.031)	(0.035)	(0.039)	(0.022)	(0.022)
Kenya	-0.003	0.104	0.148	-0.006	0.015	-0.018
	(0.063)	(0.155)	(0.149)	(0.144)	(0.040)	(0.037)
Number of observations	5,501	5,178	5,178	5,178	5,178	5,178
Panel C. Aggregate effects - Farmers who received at least one advisory message						
Full sample	0.008	0.061	0.086	0.015	-0.010	-0.019
	(0.038)	(0.058)	(0.059)	(0.057)	(0.023)	(0.020)
Panel D. Country-level effects - Farmers who received at least one advisory message						
India	0.023	-0.002	0.020	0.002	-0.033	-0.030
	(0.039)	(0.038)	(0.045)	(0.050)	(0.027)	(0.024)
Kenya	-0.018	0.205	0.238	0.045	0.041	0.005
	(0.075)	(0.168)	(0.159)	(0.144)	(0.042)	(0.038)
Number of observations	2,708	2,463	2,463	2,463	2,463	2,463
Mean of outcome - Control group:						
Full sample	4.304	2.130	1.980	1.869	0.639	0.624
India	3.699	1.266	1.212	1.188	0.666	0.627
Kenya	6.298	5.879	5.311	4.820	0.523	0.614
Country dummy	Yes	Yes	Yes	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. "***", "**", "*" indicate statistical significance at the 1, 5, and 10%, respectively.

Table 7. Labor use – Overall and by country

PBA treatment arm coefficient for:	(1) Hired male labor	(2) Hired female labor	(3) Family male labor	(4) Family female labor	(5) Own labor	(6) Number of plot visits
Panel A. Aggregate effects - All interviewed farmers						
Full sample	-2.822**	-1.745*	0.718	1.485***	-1.248	-0.220
	(1.157)	(1.055)	(0.747)	(0.553)	(1.003)	(1.199)
Panel B. Country-level effects - All interviewed farmers						
India	-1.416	-1.391	0.437	0.824**	-1.900	0.058
	(1.166)	(1.198)	(0.769)	(0.383)	(1.196)	(0.983)
Kenya	-9.229***	-3.362	2.001	4.500*	1.728	-1.486
	(3.367)	(2.083)	(2.185)	(2.434)	(1.111)	(4.912)
Number of observations	5,178	5,178	5,178	5,178	5,178	5,178
Panel C. Aggregate effects - Farmers who received at least one advisory message						
Full sample	-4.539***	-2.900**	1.645**	1.906**	-0.353	-0.335
	(1.503)	(1.226)	(0.770)	(0.837)	(1.078)	(2.109)
Panel D. Country-level effects - Farmers who received at least one advisory message						
India	-0.942	-2.397*	1.117*	0.900**	-1.326	0.776
	(1.372)	(1.302)	(0.615)	(0.378)	(1.485)	(1.127)
Kenya	-12.68	-4.041	2.841	4.186	1.851	-2.851
	(3.514)	(2.660)	(2.044)	(2.492)	(0.959)	(6.230)
Number of observations	2,463	2,463	2,463	2,463	2,463	2,463
Mean of outcome - Control group:						
Full sample	19.25	20.23	3.517	1.849	27.56	69.49
India	19.61	21.85	2.099	0.545	31.37	65.91
Kenya	17.68	13.19	9.663	7.502	11.02	84.99
Country dummy	Yes	Yes	Yes	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. “***”, “**”, “*” indicate statistical significance at the 1, 5, and 10%, respectively.

Table 8. Input use – Overall and by country

PBA treatment arm coefficient for:	(1) Cost of fertilizers	(2) Cost of pesticides	(3) Cost of fungicides	(4) Cost of herbicides	(5) Cost of irrigation
Panel A. Aggregate effects - All interviewed farmers					
Full sample	-62.99	2.418	15.49	-3.128	-32.41
	(146.3)	(18.23)	(16.41)	(7.446)	(21.80)
Panel B. Country-level effects - All interviewed farmers					
India	91.55	25.92	21.57	-0.157	-39.15
	(135.0)	(19.39)	(19.79)	(6.754)	(26.69)
Kenya	-767.6	-104.7**	-12.24	-16.68	-1.683
	(516.5)	(45.94)	(13.54)	(27.25)	(2.162)
Number of observations	5,178	5,178	5,178	5,178	5,178
Panel C. Aggregate effects - Farmers who received at least one advisory message					
Full sample	-380.2*	-20.90	2.029	-8.300	-49.22***
	(219.7)	(21.27)	(14.86)	(9.409)	(18.90)
Panel D. Country-level effects - Farmers who received at least one advisory message					
India	39.11	17.81	9.188	-4.199	-70.89***
	(155.8)	(20.37)	(19.81)	(8.055)	(27.03)
Kenya	-1,330	-108.6	-14.18	-17.59	-0.139
	(599.9)	(48.94)	(18.51)	(24.28)	(1.958)
Number of observations	2,463	2,463	2,463	2,463	2,463
Mean of outcome - Control group:					
Full sample	5,199	344.7	266.2	197.4	910.7
India	4,729	322.5	320.1	214.0	1,121
Kenya	7,238	440.9	32.32	125.7	0.000
Country dummy	Yes	Yes	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. "***", "**", "*" indicate statistical significance at the 1, 5, and 10%, respectively.

Finally, Table 9 presents results in terms of other agricultural indicators such as area cultivated, yields, and damage. We see a puzzling, statistically significant but very small decrease of 0.17 acres (out of a baseline of 3.7 acres) in the area cultivated under target crops, driven by Kenya, though this disappears once we focus on treated farmers (panels C and D). Aside from this, we find no effects in either yields or self-reported damage, either as a percentage or as an indicator capturing whether a farmer claimed to have had damage above 20%. Given the lack of effects on intermediate perception and knowledge indicators, and the very slight effects on input use, these null effects are to be expected.

When we look at the differential effects based on treatment intensity, we observe interesting effects in terms of self-reported yields and damage (Appendix Table A.6). In India, farmers receiving a higher number of advisories (as per administrative data) are reporting significantly lower yields (albeit at the 10 percent level) and they are more likely to report damage (significant at the 1 percent level). These effects are not observed in Kenya, as the interaction term for a Kenya dummy and the number of advisories is in the opposite direction as the coefficient on the number of advisories itself. We also find no significant treatment effect of receiving personalized messages in this table, except for the finding that in Panel B, an increase in the number of curative messages is associated with a higher chance of reporting crop damage; but from Panel A, we can infer that this is likely due to farmers receiving more messages – even generic – having a higher chance of reporting crop damage.

Table 9. Area cultivated, yield, and damage – Overall and by country

PBA treatment arm coefficient for:	(1) Area cultivated under target crop	(2) Crop yield	(3) Self-reported damage (%)	(4) Self-report damage is above 20%
Panel A. Aggregate effects - All interviewed farmers				
Full sample	-0.173*	-107.6	0.446	0.012
	(0.104)	(97.06)	(0.980)	(0.019)
Panel B. Country-level effects - All interviewed farmers				
India	-0.142	-124.2	0.810	0.007
	(0.134)	(114.2)	(1.100)	(0.024)
Kenya	-0.275***	-16.48	-0.738	0.027
	(0.076)	(34.15)	(2.105)	(0.025)
Number of observations	5,501	4,980	5,501	5,501
Panel C. Aggregate effects - Farmers who received at least one advisory message				
Full sample	-0.192	-140.6	1.201	0.038
	(0.136)	(98.80)	(1.348)	(0.024)
Panel D. Country-level effects - Farmers who received at least one advisory message				
India	-0.169	-172.7	2.500	0.040
	(0.212)	(129.3)	(1.723)	(0.034)
Kenya	-0.232	-40.96	-0.950	0.036
	(0.082)	(41.98)	(2.088)	(0.029)
Number of observations	2,708	2,259	2,708	2,708
Mean of outcome - Control group:				
Full sample	3.711	4,580	15.14	0.382
India	4.493	5358	11.06	0.272
Kenya	1.131	430.5	28.61	0.746
Country dummy	Yes	Yes	Yes	Yes
Crop dummies	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. "***", "**", "*" indicate statistical significance at the 1, 5, and 10%, respectively.

4.1 Empirical Strategy

Given that the effectiveness of advisories may vary by topic—depending on how familiar farmers are with specific practices or issues—we explore potential effects on specific outcomes directly related to the different advisory topics received by farmers. As advisory topics were quite heterogeneous, this is a more direct evaluation of PBA, since we should expect to see effects on specific outcomes related to the subject of advisories received before expecting to find evidence of more aggregate effects on more downstream outcome variables. To that end, we estimate Equation (4) for the following topics and their corresponding outcomes: advisories related to fertilizers, pesticides, fungicides, and herbicides (which we compare with the total costs incurred by the farmer in each of these input categories during the last season); advisories recommending specific practices for the field (which we compare against the number of these practices that a farmer knows how to implement and is willing to adopt in the near future); advisories on recommended crop-specific technologies (which we compare with the number of these technologies that the farmer used last season); and advisories recommending the use of pest- or disease-resistant crop varieties (which we measure against an indicator variable for whether the farmer used any of these varieties during the last season or is planning to use them in the next season).

Table 10 shows the results of this exercise, following a similar approach as the one for the previous set of tables focusing on treatment intensity effects by number of overall and curative advisories received. The first two columns, in addition, present estimates when pooling all outcomes together, controlling for farmer, crop, and topic dummies, effectively exploiting potential within-farmer variation in their reaction to receiving advisory messages on different topics. We see a strong negative effect on the pooled outcome from receiving a higher number of advisories, which is reinforced by being in the personalized advisories treatment arm. However, when focusing on curative advisories in column 2—only sent in the treatment arm—this effect disappears.

The remaining columns in Table 10, together with those in Table 11, report topic-specific treatment effects. We see some significant reduction on fertilizer costs when receiving a higher number of nutrient-related advisories in the treatment arm and an increase in pesticide costs when receiving a higher number of pest-related advisories in the treatment arm. Both, however, are partly offset by a coefficient of the opposite sign on the PBA treatment dummy, rendering the overall effects on farmers in the treatment arm ambiguous, which is confirmed by the non-significant coefficients on the number of curative advisories in the alternative specifications. We do not see any other impacts on the rest of the topic-specific outcomes, with the only exception of a negative impact on using a recommended crop variety in the last season, which is only significant at the 10% level (and thus would probably not survive a correction for multiple hypotheses) and could potentially be partly endogenous, with farmers that did not adopt pest- or disease-resistant varieties in the last season having received more curative advisories on those.

Table 10. Input use - Topic-specific estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Pooled topics with household fixed effects		**Cost of fertilizers**		**Cost of pesticides**		**Cost of fungicides**		**Cost of herbicides**	
Number of advisories relating to outcome received (IHS)	-84.20**		438.4***		14.71		-192.1***		-4.863	
	(34.64)		(67.95)		(26.44)		(19.55)		(5.702)	
Number of advisories * PBA treatment arm	-163.7***		-644.3***		-17.91		52.86*		2.805	
	(55.84)		(141.5)		(46.40)		(28.25)		(8.885)	
Number of curative advisories relating to outcome received (IHS)		-95.32		-680.3		19.44		275.2		4.716
		(90.73)		(844.8)		(60.15)		(201.9)		(21.59)
Number of observations	46,602	46,602	5,178	5,178	5,178	5,178	5,178	5,178	5,178	5,178
Farmer fixed effects	Yes	Yes	No	No	No	No	No	No	No	No
Topic Dummies	Yes	Yes	No	No	No	No	No	No	No	No
Crop dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Block/County dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Previous intervention dummies	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. “***”, “**”, “*” indicate statistical significance at the 1, 5, and 10%, respectively.

Table 11. Recommended practices, technologies, and crop varieties - Topic-specific estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Number of practices farmer knows how to implement		**Number of practices farmer willing to adopt**		**Number of recommended technologies used**		**Used recommended crop variety last season**		**Plans to use recommended crop variety next season**	
Number of advisories relating to outcome received (IHS)	0.018		-0.101		-0.056		-0.048		-0.027	
	(0.080)		(0.093)		(0.090)		(0.045)		(0.043)	
Number of advisories * PBA treatment arm		-0.027		0.023		0.077		-0.100*		-0.084
		(0.098)		(0.113)		(0.111)		(0.054)		(0.057)
Number of curative advisories relating to outcome received (IHS)	0.0173		-0.0209		0.0149		-0.149***		-0.112***	
	(0.0886)		(0.0872)		(0.0903)		(0.0282)		(0.0327)	
Number of observations	5,178	5,178	5,178	5,178	5,178	5,178	5,178	5,178	5,178	5,178
Crop dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. “***”, “**”, “*” indicate statistical significance at the 1, 5, and 10%, respectively.

5. The role of farmer engagement

We put forth two primary mechanisms that could have resulted in limited observed impacts of PBA. The first possible explanation is that the farmer received too few advisories to have an observable impact of personalization. However, the results from using equation (3), discussed in the previous section, seem to rule this out. The following section looks into the second possible mechanism explaining the limited effects of PBA — farmers not always reading and/or understanding the advisories.

We investigate the role of farmer engagement with the advisories through a propensity score matching (PSM) approach. In particular, we rely on survey questions on (i) whether a farmer self-reported receiving any advisories (PBA or generic) and (ii) what percentage of messages he/she read on average, to isolate the effect of engaging with advisories from that of being in the PBA treatment arm. In this section, we define farmers as being "treated" when they report *both* receiving advisories and reading at least 25% of the messages, whereby the control group includes those who either did not receive the advisories or received the advisories but did not read them. Table 12 gives a breakdown of the number of farmer-crop observations in which farmers in either treatment arm report (i) receiving advisories and (ii) reading more than 25% of them.

To address potential selection bias and improve comparability between the two groups, we use a three nearest neighbor matching approach, matching each treated farmer with three control farmers with similar propensity scores. We also seek to match treated farmers with control farmers that cultivate the same crop and belong to the original treatment arm (PBA), so we match within 14 subgroups (7 crops and two treatment arms). This method allows us to estimate the causal effects of treatment (receiving and reading advisories) on the same set of outcome variables as in the previous section.

Table 12. Engagement with advisories

	Total number of observations (farmer-crop combinations)		Total where farmers reported receiving advisories for said crop		Total where farmers reported receiving and reading more than 25% of advisories	
	PBA	Generic	PBA	Generic	PBA	Generic
India	2,057	2,146	1,587 *(77.2%)*	1,617 *(75.4%)*	1,154 *(56.1%)*	1,182 *(55.1%)*
Kenya*	1,009	999	458 *(45.4%)*	487 *(48.8%)*	413 *(40.9%)*	441 *(44.1%)*
Total	3,066	3,145	2,045 *(66.7%)*	2,104 *(66.9%)*	1,567 *(51.1%)*	1,623 *(51.6%)*

* For Kenya, farmers who reported that the champion farmers discussed the advisories with them for a specific crop have been classified as "received and read". These are the cases where champion farmers received advisories on farmers' behalf and discussed them with the farmer later.

Table 13 shows the results of the PSM analyses, specifically the estimates of the difference in outcomes between farmers who received advisories and read at least 25% of them and otherwise similar farmers who did not receive advisories or read as many of them ('Advisories read - Control')—or the effect of receiving and engaging with advisories; and the interaction of this coefficient with PBA, that is, the difference in this estimate between the original treatment arm in the control group versus our PBA treatment ('Advisories read – Treatment')—or the differential effect of receiving and engaging with personalized advisories relative to generic ones.

Having received and read at least 25% of advisories is associated with an improvement in perceptions of the advisory; particularly in helping farmers learn new information, saving time, lowering costs, as well as improving crop quality and yields, regardless of the type of advisories received (generic or personalized). In Panel B, we find these differences to be substantially more pronounced in Kenya than in India. The differences in perceptions between farmers who read at least 25 percent of the advisories and otherwise similar farmers who did not recall receiving or reading as many messages disaggregated by both country and original treatment arm (i.e. type of advisory received) in Panel C tell a similar story, with weaker effects in India (that are mostly non-significant in the personalized treatment arm) and stronger effects in Kenya (with no statistically significant differences across the PBA and generic groups). Overall, this suggests that PBA treatment does not add to the improvement in perceptions even for the farmers who had better engagement with advisories.

Table 14 shows the PSM effects on outcome variables related to knowledge and adoption of recommended practices and technologies. Similar to Table 13, we see statistically-significant differences in these outcomes between farmers who received advisories and read at least 25 percent of them and comparable farmers who did not receive advisories or read as many of them, with the former group on average exhibiting higher knowledge scores, willing to implement a larger number of recommended practices, and reporting using more recommended technologies in the previous season. In contrast to the above results, whereas differences related to farmers' perceptions were stronger in the Kenya sample, knowledge- and adoption-related differences are primarily driven by the India sample. However, as before, the differences between more and less engaged farmers do not seem to be larger in the personalized advisories treatment compared to the generic one.

Summarizing, the results from the propensity score matching analysis show that the lack of effects of PBA described in the previous section do not seem to be due to farmers not receiving advisories or engaging with them. Indeed, farmers who received and engaged with advisories reported better outcomes in terms of perception, knowledge, and technology adoption relative to similar farmers who did not receive or read them; but these improvements were not stronger when receiving personalized advisories than when receiving generic ones. In other words, farmers in both the PBA treatment group (personalized advisories) and the control group (generic advisories) benefited from reading them and did so to roughly the same extent.

As described above, however, many advisory messages in the personalized treatment arm were comparable to those in the generic treatment arm. For instance, when experts reviewing the pictures did not see any clear challenges in the field, they would send back a pre-written encouragement message or one with generic preventative advice. In this sense, it is possible that farmers in the PBA treatment arm simply did not interpret the advisories as being tailored to pictures of their fields, particularly considering the overall low self-reported fraction of messages read. To explore this, we performed a similar PSM analysis focusing on farmers who reported perceiving the advisories as being personalized. When contrasting these farmers' outcomes with those of comparable farmers who did not perceive the advisories being tailored to their crop needs, we find significant positive differences in terms of perception, knowledge, and adoption outcomes.[4] These results may indicate that when the advice received feels appropriate and relevant to their specific context, farmers are more likely to engage with it and apply it successfully. However, since these findings are not based on experimental variation, they could be subject to biases and should thus be interpreted with caution.

A final, related aspect to the issue of farmer engagement is whether farmers actually understood advisories. During the survey, when we asked farmers if they had understood the advisory messages, only around 60% of farmers who reported receiving the messages indicated that they had understood them. In Kenya, when the answer was negative, the main reason cited was a lack of literacy. Unfortunately, the small sample size of farmers who reported receiving, reading, and understanding advisories prevent us from doing additional analyses in this regard.

[4] These results are unreported due to space considerations but are available upon request.

Table 13. Perception- All effects

Treatment (read advisories) arm coefficient for:	(1) Aggregate measure of perception (6 items)	(2) Advisories helped to: learn new information	(3) Advisories helped to: minimize risks	(4) Advisories helped to: save time	(5) Advisories helped to: lower costs	(6) Advisories helped to: improve the crop quality	(7) Advisories helped to: improve yields
Panel A. Aggregate effects – All interviewed farmers, by original treatment arm							
Read advisories – Generic	0.816***	0.143**	0.040	0.086*	0.140**	0.231***	0.177***
	(0.301)	(0.059)	(0.056)	(0.050)	(0.054)	(0.068)	(0.064)
Read advisories – Personalized	0.426*	0.114**	-0.022	0.073*	0.104**	0.094*	0.062
	(0.242)	(0.050)	(0.050)	(0.044)	(0.050)	(0.056)	(0.047)
p-val (Personalized-Generic)	0.314	0.717	0.414	0.844	0.627	0.118	0.148
Panel B. Country-level effects – All interviewed farmers							
Read advisories - India	0.405**	0.102**	-0.047	0.034	0.098**	0.121**	0.097**
	(0.202)	(0.040)	(0.038)	(0.034)	(0.039)	(0.048)	(0.043)
Read advisories - Kenya	3.056***	0.424***	0.642***	0.601***	0.397***	0.626***	0.366***
	(0.459)	(0.104)	(0.096)	(0.063)	(0.096)	(0.086)	(0.105)
Panel C. Country-level effects – All interviewed farmers, by original treatment arm							
Read advisories – Generic – Kenya	3.199***	0.431***	0.675***	0.607***	0.445***	0.651***	0.39***
	(0.521)	(0.116)	(0.108)	(0.078)	(0.104)	(0.096)	(0.114)
Read advisories – Personalized – Kenya	2.848***	0.413***	0.597***	0.594***	0.338***	0.581***	0.324***
	(0.511)	(0.112)	(0.107)	(0.081)	(0.108)	(0.102)	(0.112)
Read advisories – Generic – India	0.557*	0.111*	-0.030	0.030	0.105*	0.186**	0.154**
	(0.308)	(0.061)	(0.056)	(0.051)	(0.057)	(0.072)	(0.067)
Read advisories – Personalized – India	0.262	0.0938*	-0.0631	0.0381	0.0902*	0.0596	0.043
	(0.241)	(0.051)	(0.049)	(0.043)	(0.051)	(0.057)	(0.048)
p-val (Personalized -Generic) – Kenya	0.464	0.851	0.421	0.890	0.258	0.463	0.463
p-val (Personalized -Generic) – India	0.439	0.824	0.648	0.896	0.839	0.155	0.167
Number of observations	3,503	3,503	3,503	3,503	3,503	3,503	3,503
Mean of outcome – Control group: Full Sample	3.177	0.552	0.501	0.343	0.631	0.490	0.660
Mean of outcome – Control group: India	3.268	0.551	0.529	0.366	0.644	0.514	0.664
Mean of outcome – Control group: Kenya	2.161	0.568	0.184	0.084	0.481	0.229	0.616
Country dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Block (India) / County (Kenya) dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummies for other (orthogonal) interventions	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. "***", "**", "*" indicate statistical significance at the 1, 5, and 10%, respectively. Means are weighted using PSM generated pweights. Note: Advisories read refers to the coefficient representing the difference in outcomes between farmers who read at least 25% of the advisories and those who did not, based on a matched sample.

Table 14. Knowledge and Adoption- All effects

Treatment (read advisories) arm coefficient for:	(1) Knowledge score (6 items)	(2) No. of practices farmer knows how to implement	(3) No. of practices farmer willing to adopt	(4) No. of recommended technologies used	(5) Used recommended crop variety last season	(6) Plans to use recommended crop variety next season
Panel A. Aggregate effects – All interviewed farmers, by original treatment arm						
Read advisories – Generic	0.128	0.088	0.156*	0.171**	0.015	0.020
	(0.082)	(0.083)	(0.085)	(0.068)	(0.024)	(0.023)
Read advisories – Personalized	0.131**	0.074	0.112**	0.130***	0.020	0.037
	(0.062)	(0.052)	(0.056)	(0.049)	(0.025)	(0.024)
p-val (Personalized -Generic)	0.984	0.870	0.652	0.621	0.871	0.593
Panel B. Country-level effects – All interviewed farmers						
Read advisories - India	0.209***	0.096***	0.104***	0.123***	0.015	0.024
	(0.039)	(0.032)	(0.029)	(0.030)	(0.019)	(0.018)
Read advisories - Kenya	-0.121	0.006	0.289	0.290	0.030	0.052
	(0.168)	(0.250)	(0.273)	(0.200)	(0.047)	(0.045)
Panel C. Country-level effects – All interviewed farmers, by original treatment arm						
Read advisories – Generic – Kenya	-0.290	-0.070	0.300	0.293	0.031	0.064
	(0.227)	(0.299)	(0.332)	(0.250)	(0.056)	(0.052)
Read advisories – Personalized – Kenya	0.085	0.105	0.276	0.287	0.029	0.038
	(0.184)	(0.307)	(0.325)	(0.247)	(0.056)	(0.057)
Read advisories – Generic – India	0.275***	0.125**	0.124**	0.144***	0.011	0.010
	(0.063)	(0.061)	(0.058)	(0.053)	(0.025)	(0.023)
Read advisories – Personalized – India	0.143**	0.067	0.084*	0.103**	0.018	0.038
	(0.061)	(0.044)	(0.046)	(0.040)	(0.027)	(0.025)
p-val (Personalized -Generic) – Kenya	0.135	0.623	0.928	0.970	0.994	0.682
p-val (Personalized -Generic) – India	0.163	0.480	0.625	0.559	0.829	0.408
Number of observations	5,448	4,840	4,840	4,840	4,840	4,840
Mean of outcome – Control group: Full Sample	4.138	1.967	1.808	1.692	0.633	0.602
Mean of outcome – Control group: India	3.585	1.229	1.185	1.155	0.653	0.605
Mean of outcome – Control group: Kenya	5.850	5.959	5.177	4.596	0.527	0.588
Country dummy	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Block (India) / County (Kenya) dummies	Yes	Yes	Yes	Yes	Yes	Yes
Dummies for other (orthogonal) interventions	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. "***", "**", "*" indicate statistical significance at the 1, 5, and 10%, respectively. Means are weighted using PSM generated pweights. Note: Advisories read refers to the coefficient representing the difference in outcomes between farmers who read at least 25% of the advisories and those who did not, based on a matched sample.

6. Conclusions

Improving agricultural productivity is crucial for smallholder farmers in developing countries facing climate risks and limited access to resources. Digital agricultural extension services, powered by smartphone technology and potentially AI, hold the promise of cost-effective, personalized advisories for farmers worldwide. However, there is limited evidence on whether personalized advisories outperform generic ones. Providing evidence around this question can guide future investments in agricultural technology, ensuring resources are directed toward the most effective extension models.

We rely on a large-scale randomized controlled trial in 257 villages in India and Kenya, around an intervention that uses smartphone pictures to provide image-based personalized advisories to farmers over three agricultural seasons. In particular, farmers in randomly-selected treatment villages were provided with personalized picture-based advisories (PBA) and those in the remaining villages were provided with generic advisories (not tailored to the conditions visible in the pictures from their fields).

We find no significant effects of personalized advisories over generic ones in terms of a range of outcomes, including farmers' perceptions about the advisories, their level of agricultural knowledge, adoption and willingness to adopt recommended agricultural practices and technologies, input use, or downstream agricultural outcomes such as yields or damage. We do find limited impacts of personalized advisories on labor and input use, whereby farmers who were randomly assigned to receive personalized advisories hired less labor and used more family labor to cultivate their farms. A plausible explanation for this could be the nature of the intervention, which requires farmers to send in photos of their fields on a regular basis, potentially encouraging farmers to combine these visits with activities for which they normally would have hired a laborer.

Farmers not benefiting from personalized messages could reflect implementation challenges, since a lot of the messages sent to farmers in the personalized advisories treatment arm were of a preventive nature or gave no specific advice. However, even among farmers receiving a larger number of more targeted curative advisories we still do not see significant effects.

To aid the understanding of the mechanisms underlying such null results, we conduct quasi-experimental propensity score matching analyses to test whether farmer engagement with advisories has a role in explaining these. Indeed, farmers who report having received advisories and reading a considerable fraction of them show better outcomes relative to comparable farmers who did not receive or read advisories, but this effect is of a similar magnitude regardless of whether the advisories were personalized or generic. These findings highlight that increasing farmers' engagement through digital extension services may require more than tailoring content to the situation in their fields.

Lastly, we also report evidence on farmers not always being able to comprehend the advisories. This suggests that future efforts should explore more accessible delivery channels, such as interactive voice response (IVR) systems or audiovisual media, which could simplify information dissemination. Alternatively, targeting digitally-literate farmers with such innovations while leveraging traditional extension services for less tech-savvy farmers could enhance their overall effectiveness.

Our study uncovers important gaps in understanding how personalized advisories impact farmer behavior and, ultimately, their agricultural outcomes. While personalization can theoretically enhance the advisories' relevance, its success depends on farmers' ability to access, understand, and act on the information provided. Even under optimal tailoring, limited digital literacy, varying levels of trust in advisory sources, and challenges around consistent engagement may undermine the advisories' effectiveness. Additionally, SMS- and app-based communication may not be sufficiently interactive or accessible for all farmers, limiting the potential impact of text-based digital extension.

Future research should explore how to make personalized advisories more engaging and easier to understand. Testing interactive formats such as voice-based advisories or audiovisual tools could improve accessibility and comprehension. Studies could also examine strategies to increase farmers' trust and sustained engagement, such as integrating digital advisories with in-person support from local extension agents or farmer champions. This combined approach could bring personalization to deliver meaningful, scalable impacts in diverse agricultural contexts.

Our findings also contribute to the broader AI literature by underscoring the limitations of digital agricultural advisory platforms. While AI-enabled tools offer promising avenues for personalized extension services, they require careful design to achieve broad accessibility, encourage farmer engagement, and ensure understanding among farmers with diverse literacy and digital skills. The limited impacts observed in our study suggest that AI-driven solutions would need to go beyond tailoring content to individual circumstances — directly addressing farmers' ability to comprehend and act on the advice received. A hybrid model that combines automated advisories with the interaction with human experts for complex queries, could strike a balance between cost-effectiveness and personalized support, making digital agricultural extension more inclusive and impactful.

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Appendix

Table A.1. Program participation – By number of advisories

PBA treatment arm coefficient for:	(1) Received at least one advisory (self-reported)	(2) Advisories were tailored to crop's needs (self-reported)
Panel A. All advisory types		
PBA treatment arm	0.021	0.016
	(0.029)	(0.026)
Kenya	-0.413***	-0.395***
	(0.077)	(0.084)
Number of advisories received (IHS)	0.060***	0.020**
	(0.011)	(0.008)
PBA treatment * Number of adv.	-0.024*	-0.019*
	(0.014)	(0.010)
Kenya * Number of adv.	-0.043**	0.003
	(0.022)	(0.024)
PBA treatment* Kenya	0.030	0.079
	(0.051)	(0.056)
PBA treatment * Kenya * Number of adv.	-0.002	-0.019
	(0.026)	(0.028)
Panel B. Only curative advisories		
PBA treatment arm	-0.010	-0.008
	(0.024)	(0.023)
Kenya	-0.440***	-0.373***
	(0.070)	(0.074)
Number of curative advisories received (IHS)	0.095***	0.039*
	(0.017)	(0.023)
PBA treatment* Kenya	0.047	0.073*
	(0.040)	(0.041)
Kenya * Number of curative adv.	-0.122***	-0.071**
	(0.027)	(0.031)
Number of observations	5,501	5,501
Mean of outcome - Control group:		
Full sample	0.638	0.440
India	0.753	0.492
Kenya	0.258	0.269
Crop dummies	Yes	Yes
Baseline controls	Yes	Yes
Block/County dummies	Yes	Yes
Previous intervention dummies	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. "***", "**", "*" indicate statistical significance at the 1, 5, and 10%, respectively.

Table A.2. Farmers' perception of advisories – By number of advisories

	(1) **Aggregate measure of perception (6 items)**	(2) **Advisories helped to: learn new information**	(3) **Advisories helped to: minimize risks**	(4) **Advisories helped to: save time**	(5) **Advisories helped to: lower costs**	(6) **Advisories helped to: improve the quality of the crop**	(7) **Advisories helped to: improve yields**
Panel A. All advisory types							
PBA treatment arm	-0.059	-0.018	0.020	-0.017	-0.024	-0.005	-0.015
	(0.118)	(0.023)	(0.036)	(0.036)	(0.021)	(0.035)	(0.034)
Kenya	-0.235	0.287**	-0.033	-0.308**	-0.364**	0.128	0.054
	(0.583)	(0.111)	(0.146)	(0.153)	(0.156)	(0.128)	(0.114)
Number of advisories received	-0.004	0.007	0.006	-0.005	-0.015*	0.006	-0.004
(IHS)	(0.028)	(0.007)	(0.009)	(0.009)	(0.008)	(0.009)	(0.010)
PBA treatment * Number of adv.	-0.046	-0.011	-0.005	0.006	0.002	-0.023*	-0.016
	(0.041)	(0.010)	(0.012)	(0.013)	(0.009)	(0.013)	(0.012)
Kenya * Number of adv.	-0.018	0.001	0.006	-0.018	0.007	0.001	-0.015
	(0.179)	(0.036)	(0.036)	(0.042)	(0.034)	(0.038)	(0.033)
PBA treatment* Kenya	-0.217	0.001	-0.065	0.073	-0.167*	-0.032	-0.026
	(0.426)	(0.089)	(0.094)	(0.116)	(0.092)	(0.096)	(0.084)
PBA treatment * Kenya * Number	-0.066	-0.012	-0.022	-0.073	0.051	-0.015	0.006
of adv.	(0.240)	(0.052)	(0.047)	(0.061)	(0.048)	(0.053)	(0.046)
Panel B. Only curative advisories							
PBA treatment arm	-0.120	-0.034*	0.012	-0.013	-0.022	-0.030	-0.033
	(0.107)	(0.019)	(0.035)	(0.030)	(0.019)	(0.033)	(0.032)
Kenya	-0.291	0.285***	-0.014	-0.344***	-0.364**	0.132	0.015
	(0.448)	(0.089)	(0.126)	(0.122)	(0.148)	(0.107)	(0.100)
Number of curative advisories	0.057	0.038*	0.026	0.044*	0.015	-0.048	-0.018
received (IHS)	(0.082)	(0.022)	(0.033)	(0.022)	(0.022)	(0.033)	(0.037)
PBA treatment* Kenya	-0.141	0.048	-0.083	0.035	-0.153*	-0.012	0.023
	(0.298)	(0.060)	(0.072)	(0.086)	(0.078)	(0.074)	(0.066)
Kenya * Number of curative adv.	-0.225	-0.098*	-0.043	-0.108*	0.047	-0.004	-0.019
	(0.216)	(0.050)	(0.052)	(0.055)	(0.051)	(0.054)	(0.052)
Number of observations	3,548	3,548	3,548	3,548	3,548	3,548	3,548
Mean of outcome - Control group:							
Full sample	3.523	0.618	0.477	0.383	0.696	0.618	0.732
India	3.430	0.596	0.453	0.363	0.690	0.605	0.724
Kenya	4.417	0.833	0.708	0.571	0.750	0.738	0.815
Crop dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. "***", "**", "*" indicate statistical significance at the 1, 5, and 10%, respectively.

Table A.3. Knowledge and adoption – By number of advisories

	(1) **Knowledge score (6 items)**	(2) **Number of practices farmer knows how to implement**	(3) **Number of practices farmer willing to adopt**	(4) **Number of recommended technologies used**	(5) **Used recommended crop variety last season**	(6) **Plans to use recommended crop variety next season**
Panel A. All advisory types						
PBA treatment arm	0.006	-0.049	-0.046	-0.047	-0.011	-0.025
	(0.037)	(0.037)	(0.037)	(0.040)	(0.024)	(0.025)
Kenya	1.008***	3.606***	2.123***	1.805***	-0.194	-0.030
	(0.191)	(0.346)	(0.331)	(0.296)	(0.128)	(0.108)
Number of advisories received (IHS)	0.004	-0.002	-0.012	-0.009	0.005	0.002
	(0.009)	(0.011)	(0.011)	(0.010)	(0.006)	(0.007)
PBA treatment * Number of adv.	0.001	0.015	0.025*	0.019	-0.008	-0.001
	(0.014)	(0.015)	(0.014)	(0.014)	(0.008)	(0.008)
Kenya * Number of adv.	-0.016	-0.052	0.051	0.073	-0.015	-0.015
	(0.058)	(0.116)	(0.101)	(0.091)	(0.024)	(0.024)
PBA treatment* Kenya	0.009	0.143	0.111	0.028	-0.068	-0.070
	(0.138)	(0.307)	(0.309)	(0.313)	(0.078)	(0.078)
PBA treatment * Kenya * Number of adv.	-0.013	-0.011	0.025	-0.010	0.063*	0.046
	(0.073)	(0.155)	(0.159)	(0.151)	(0.036)	(0.036)
Panel B. Only curative advisories						
PBA treatment arm	0.007	-0.031	-0.019	-0.026	-0.019	-0.027
	(0.032)	(0.031)	(0.035)	(0.040)	(0.023)	(0.022)
Kenya	0.980***	3.498***	2.197***	1.915***	-0.226**	-0.061
	(0.134)	(0.270)	(0.291)	(0.253)	(0.113)	(0.094)
Number of curative advisories received (IHS)	-0.010	-0.010	-0.004	-0.004	-0.014	0.000
	(0.027)	(0.050)	(0.047)	(0.047)	(0.028)	(0.030)
PBA treatment* Kenya	0.034	0.255	0.164	0.104	0.013	-0.018
	(0.086)	(0.218)	(0.241)	(0.253)	(0.064)	(0.061)
Kenya * Number of curative adv.	-0.029	-0.089	0.006	-0.065	0.031	0.021
	(0.053)	(0.150)	(0.167)	(0.159)	(0.043)	(0.043)
Number of observations	5,501	5,178	5,178	5,178	5,178	5,178
Mean of outcome - Control group:						
Full sample	4.304	2.130	1.980	1.869	0.639	0.624
India	3.699	1.266	1.212	1.188	0.666	0.627
Kenya	6.298	5.879	5.311	4.820	0.523	0.614
Crop dummies	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. "***", "**", "*" indicate statistical significance at the 1, 5, and 10%, respectively.

Table A.4. Labor use – By number of advisories

	(1) Hired male labor	(2) Hired female labor	(3) Family male labor	(4) Family female labor	(5) Own labor	(6) Number of plot visits
Panel A. All advisory types						
PBA treatment arm	-1.775	-1.187	0.165	0.917*	-2.328*	-0.389
	(1.345)	(1.504)	(1.044)	(0.536)	(1.294)	(1.125)
Kenya	-18.94***	-18.36***	-4.868	1.026	-43.90***	-58.75***
	(5.692)	(4.771)	(5.236)	(4.538)	(4.588)	(13.03)
Number of advisories received (IHS)	0.041	0.245	-0.120	0.128	-0.502	-0.158
	(0.342)	(0.418)	(0.238)	(0.123)	(0.312)	(0.222)
PBA treatment * Number of adv.	0.322	-0.186	0.247	-0.086	0.391	0.395
	(0.499)	(0.573)	(0.365)	(0.209)	(0.452)	(0.372)
Kenya * Number of adv.	2.318	0.052	-0.488	1.180	0.691	8.966**
	(1.995)	(1.429)	(1.855)	(1.359)	(1.485)	(3.772)
PBA treatment* Kenya	4.101	-0.198	1.074	7.075*	5.835	10.340
	(5.548)	(2.869)	(5.674)	(4.261)	(3.881)	(6.982)
PBA treatment * Kenya * Number of adv.	-7.048***	-0.967	0.187	-1.934	-1.432	-6.911*
	(2.650)	(1.705)	(2.597)	(1.972)	(1.753)	(4.103)
Panel B. Only curative advisories						
PBA treatment arm	-1.538	-1.375	0.426	0.865**	-1.889	0.006
	(1.160)	(1.193)	(0.768)	(0.385)	(1.200)	(0.990)
Kenya	-13.45***	-17.76***	-5.797*	3.782	-42.85***	-41.38***
	(4.298)	(3.745)	(3.269)	(3.016)	(3.154)	(9.493)
Number of curative advisories received (IHS)	2.050	-0.264	0.177	-0.701	-0.191	0.850
	(1.573)	(2.884)	(1.197)	(0.458)	(1.200)	(0.885)
PBA treatment* Kenya	-7.321*	-2.532	0.880	2.547	3.596*	-4.303
	(4.375)	(2.432)	(3.334)	(2.973)	(1.941)	(4.192)
Kenya * Number of curative adv.	-2.352	0.711	0.393	1.593	0.208	1.456
	(2.491)	(3.222)	(2.178)	(1.646)	(1.352)	(2.293)
Number of observations	5,178	5,178	5,178	5,178	5,178	5,178
Mean of outcome - Control group:						
Full sample	19.25	20.23	3.517	1.849	27.56	69.49
India	19.61	21.85	2.099	0.545	31.37	65.91
Kenya	17.68	13.19	9.663	7.502	11.02	84.99
Crop dummies	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. “***”, “**”, “*” indicate statistical significance at the 1, 5, and 10%, respectively.

Table A.5. Input use – By number of advisories

	(1) Cost of fertilizers	(2) Cost of pesticides	(3) Cost of fungicides	(4) Cost of herbicides	(5) Cost of irrigation
Panel A. All advisory types					
PBA treatment arm	77.14	26.93	26.56	0.369	-30.83
	(174.5)	(25.89)	(26.72)	(7.455)	(30.38)
Kenya	3,412***	583.4***	-198.7***	568.5***	-1,835***
	(1,028)	(185.4)	(50.84)	(208.7)	(69.44)
Number of advisories received (IHS)	16.22	0.089	2.298	0.056	-15.81*
	(40.47)	(6.174)	(6.516)	(2.287)	(8.310)
PBA treatment * Number of adv.	12.11	-0.934	-4.508	-0.463	-7.264
	(68.29)	(9.194)	(9.358)	(2.907)	(10.26)
Kenya*Number of adv.	891.0***	24.90	7.959	-11.37	14.59*
	(304.5)	(35.61)	(19.21)	(26.87)	(8.384)
PBA treatment* Kenya	873.9	-113.3	-15.95	-32.29	25.48
	(802.4)	(93.90)	(37.81)	(61.68)	(30.79)
PBA treatment * Kenya * Number of adv.	-1,000**	-9.272	-8.666	9.155	9.271
	(457.2)	(45.15)	(19.89)	(28.56)	(10.46)
Panel B. Only curative advisories					
PBA treatment arm	70.56	23.60	18.61	-0.115	-36.47
	(134.6)	(19.14)	(19.70)	(6.769)	(26.79)
Kenya	5,095***	629.7***	-182.2***	545.4**	-1,824***
	(899.6)	(170.1)	(38.45)	(213.7)	(68.38)
Number of curative advisories received (IHS)	358.7	39.04	50.04	-0.639	-45.31
	(295.8)	(66.68)	(68.33)	(8.250)	(28.98)
PBA treatment* Kenya	-91.99	-140.0*	-27.76	-6.048	32.86
	(610.8)	(77.77)	(23.13)	(43.60)	(27.30)
Kenya * Number of curative adv.	-970.4**	-29.47	-52.53	-7.983	46.85
	(445.1)	(77.57)	(68.71)	(21.45)	(29.14)
Number of observations	5,178	5,178	5,178	5,178	5,178
Mean of outcome - Control group:					
Full sample	5,199	344.7	266.2	197.4	910.7
India	4,729	322.5	320.1	214.0	1,121
Kenya	7,238	440.9	32.32	125.7	0.000
Crop dummies	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. "***", "**", "*" indicate statistical significance at the 1, 5, and 10%, respectively.

Table A.6. Area cultivated, yield, and damage – By number of advisories

	(1) **Area cultivated under target crop**	(2) **Crop yield**	(3) **Self-reported damage (%)**	(4) **Self-report damage is above 20%**
Panel A. All advisory types				
PBA treatment arm	-0.075	-146.2	0.247	-0.001
	(0.141)	(136.8)	(0.862)	(0.022)
Kenya	-2.859***	-2,142***	40.05***	0.435***
	(0.328)	(294.0)	(7.011)	(0.094)
Number of advisories received (IHS)	0.077	-68.02*	3.659***	0.075***
	(0.055)	(37.21)	(0.436)	(0.010)
PBA treatment * Number of adv.	-0.061	20.66	0.458	0.007
	(0.071)	(51.08)	(0.547)	(0.012)
Kenya*Number of adv.	-0.040	106.1***	-5.621***	-0.064**
	(0.073)	(40.86)	(1.794)	(0.025)
PBA treatment* Kenya	-0.372*	188.9	-3.682	0.024
	(0.204)	(139.9)	(4.986)	(0.056)
PBA treatment * Kenya * Number of adv.	0.170*	-56.78	1.075	-0.003
	(0.102)	(55.53)	(2.386)	(0.030)
Panel B. Only curative advisories				
PBA treatment arm	-0.153	-91.736	-0.323	-0.012
	(0.133)	(108.1)	(1.054)	(0.023)
Kenya	-2.873***	-1,988***	32.68***	0.385***
	(0.315)	(282.8)	(5.824)	(0.080)
Number of curative advisories received (IHS)	0.195	-547.9	19.09***	0.316***
	(0.219)	(393.3)	(2.143)	(0.033)
PBA treatment* Kenya	-0.242	65.41	-0.089	0.038
	(0.167)	(114.1)	(3.214)	(0.042)
Kenya * Number of curative adv.	-0.090	557.2	-19.37***	-0.316***
	(0.225)	(392.6)	(2.603)	(0.039)
Number of observations	5,501	4,980	5,501	5,501
Mean of outcome - Control group:				
Full sample	3.711	4,580	15.14	0.382
India	4.493	5,358	11.06	0.272
Kenya	1.131	430.5	28.61	0.746
Crop dummies	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes
Block/County dummies	Yes	Yes	Yes	Yes
Previous intervention dummies	Yes	Yes	Yes	Yes

Note: Standard errors, clustered at the village level, are in parentheses. “***”, “**”, “*” indicate statistical significance at the 1, 5, and 10%, respectively.

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Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org