Assessing feasibility and effects of personalized remote advisories based on smartphone pictures

A formative evaluation in India

Working Paper No. 406

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

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Abstract

This paper provides a formative evaluation of picture-based advisories (PBA), using a cluster randomized trial in the states of Punjab and Haryana in northern India. The study randomly assigned 203 villages to one of three treatment arms: a control group, in which farmers received generic agricultural advisories; a PBA treatment arm, in which farmers received not only generic advisories but also PBA messages personalized based on smartphone images of their crops; and a treatment arm in which farmers received picture-based insurance (PBI) coverage for visible damage to insured crops in addition to the generic and PBA messages. We find high participation among all groups of farmers, regardless of potential digital divides, indicating feasibility of an inclusive PBA approach. Moreover, PBA improved farmers' knowledge around good agricultural practices. Although this did not translate into increased adoption of recommended practices in the short run, farmers do report that the advisory service helps them reduce risk, providing a business case for bundling this service with insurance.

Keywords

agricultural extension; personalized advisories, digital technology; smartphones, crop insurance, India

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Contents

Introduction

Improving agricultural productivity and promoting sustainable agricultural development is a pressing concern for developing countries with higher rates of food insecurity, malnutrition, and rural poverty. Despite achieving remarkable productivity growth since the 1960s and 1970s, productivity gaps between low-income and high-income countries persist, along with large heterogeneity across crops and regions (Steensland 2021). Improvements in productivity are also increasingly threatened by climate change. In India, for example, rising temperatures and changing rainfall patterns could reduce yields of major crops by as much as 10 percent by 2035 (Naresh et al. 2017). As smallholder farmers form a large proportion of rural poor, improving smallholders' agricultural productivity through technology adoption has the potential to reduce both poverty and vulnerability to shocks, indirectly improving human development outcomes. Yet, adoption of recommended agricultural practices and technologies has historically been slow or uneven in developing countries (Sunding and Zilberman 2001).

Past studies have found that poor access to finance, uninsured risk, and imperfect information play a significant role in hindering the adoption of yield-improving and resilience-enhancing technologies (Feder, Just, and Zilberman 1985, Foster and Rosenzweig 1995, Foster and Rosenzweig 2010, and Jack 2013 with an overview of the literature)**,** perpetuating farming systems limited by low technology adoption, inefficient input use, and exposure to production and price risks. Farmers face uncertainty not only about how a new technology or agricultural practice affects yields in their field, but also about weather realizations during the growing season and how these interact with any new technologies they may consider adopting. This uncertainty prompts risk-averse farmers to make sub-optimal production decisions and systematically under-invest in technology, especially when faced with additional constraints around access to land, labor, and capital typical among smallholders (Magruder 2018).

Extension services that transfer knowledge and promote efficient and sustainable agricultural practices and technologies in rural low-income settings can therefore play a crucial role in improving smallholder farmers' productivity and incomes. Moreover, these services can help accelerate climate adaptation and the transition towards more resource-efficient production systems (World Bank 2007). Traditionally provided through public extension systems, extension services are increasingly relying on mobile phones. The recent advent of ICT, digital technologies, and big data has served to improve agricultural services, including extension, contributing to better outcomes around smallholder farmers' adoption of recommended practices and technologies. In particular, ICTs have lowered the costs of extension and facilitated better communication between beneficiary farmers and extension agents, as well as with peers from farmers' own social networks, enabling the dissemination of more accurate and interactive advisories. Nevertheless, the evidence on the impacts of agricultural extension on adoption of improved technologies and management practices is mixed, with both evidence showing substantial impact (de Janvry and Sadoulet 2020) and limited effects on technology adoption and yields (Nakasone et al 2014, Baumueller 2015, Deichmann et al. 2016). In a meta-analysis of six ICT based studies, Fabregas, Kremer, & Schilbach (2019) find that providing mobile-based advisory on average improves the odds of a farmer purchasing the recommended input by 22 percent, increases yields by approximately 4 percent, and provides a return on investment of up to ten times. However, they find that results are context-specific and could vary among farmers with different characteristics and across different advisory modes. Other recent evaluations of localized, interactive mobile advisories find that they improve the adoption of new crops and technology (Campenhout et al. 2017, Cole and Fernando 2021, Larochelle et al. 2019). However, advisory programs remain limited in their ability to overcome behavioral and financial barriers to adoption (Aker, Ghosh, and Burrell 2016). Aker (2011) notes that the effectiveness of traditional extension seems to have been hampered by large costs and poor reach, and by the presence of other barriers to adoption such as lack of access to finance or markets.

This paper analyzes the potential for improving advisories and strengthening their impact by relying on smartphone technology. In particular, it tests whether the above challenges can be overcome by moving towards personalized remote advisory services that tailor recommendations based on smartphone images of a farmer's crops. In addition, it explores whether bundling advisory services with crop insurance can help reduce risk-related barriers to adoption of recommended practices and technologies. To do this, we rely on a novel insurance product, picture-based insurance (PBI), that minimizes basis risk by paying out when farmers suffer visible damage, as verified from a stream of smartphone images submitted throughout the entire agricultural season (see Ceballos, Kramer, and Robles 2019).

Using a cluster randomized trial in which villages were randomly assigned into treatment and control groups, we evaluate the effects of a personalized advisory service on farmers' knowledge, perceptions of advisories, and adoption of agricultural practices. In the control group, farmers received standard generic messages about good agricultural practices via SMS and interactive voice response (IVR). In the treatment group, in addition to generic messages, farmers received personalized advisories based on submitted photos of their crops. Further, half of the villages in the treatment group were randomly selected to receive a crop insurance policy, which paid out in case of extreme heat or visible damage to the crops.

We find that personalized advisories improved farmers' knowledge around good agricultural practices and farmers believed these to be more relevant and effective than generic advisory messages. However, improvements in knowledge did not translate on increased adoption of suggested practices, even though farmers reported that personalized advisories helped them reduce risk more than other sources of information that they could access. This is a relevant outcome for insurance providers, who have a direct incentive to reduce farmers' risk exposure, and thus the extent of crop damage and expected payouts. We also observe increased willingness to pay for advisories and farmer participation —as measured from the number of submitted images—when advisories are bundled with the insurance product, suggesting that there is a business case for combining these two forms of ICT-based innovations into a picture-based insurance-advisory bundle.

This paper relates to three areas in the literature. First, the paper adds to a growing literature on the impacts of ICT-based advisories to reduce information constraints (see, for instance, Cole and Fernando 2021). Traditional in-person extension models are by definition personalized and perceived to be useful by farmers but are usually subject to a high marginal cost and many farmers lack access to them. ICT-based advisories, in contrast, can be delivered at a much lower cost but are often provided in the form of one-way generic advisories, unable to capture heterogeneity in farmer, crop, and farming practices within a broader geographic region. While phone-based advisories have been successfully used to deliver localized advisories (Cole and Fernando 2021), evidence on newer more tailored and interactive advisories is limited. Moving from localized messages (tailored for an average farmer in a broad geographical region) to personalized messages (based on a farmer's individual situation) could make advisories more appropriate and relevant, and the participatory, two-way nature of these picture-based advisories could result in farmers paying more attention the messages. We find that although these advisories may improve knowledge and self-reported satisfaction with the service, they do not necessarily lead to increased adoption of recommended practices and technologies.

Second, the paper relates to a smaller literature on business models for providing ICT-based advisories. Given that information is a public good, an important question in the design of extension systems is who will be paying for the costs of designing and implementing advisory services. In this paper, we explore whether there is a business case for bundling advisories with insurance, with an insurance provider paying for the service and potentially passing on a portion of the cost to farmers. Our findings suggest that insurance providers could use advisories to lower farmer's risk exposure and thereby expected insurance payouts, and that the provision of advisories may increase farmers' willingness to pay and thus demand for insurance. At the same time, combining advisories with insurance could potentially help lower the risk of adoption of recommended practices, further improving the business case for bundling. Unfortunately, since our study did not include an insurance-only treatment arm, we cannot quantify the impacts of providing advisories in the context of an insurance scheme. This remains an area for future research.

A final area of the literature related to this paper are studies addressing barriers to technology adoption and improved agricultural risk management through packaged interventions. Increased financial inclusion through, for instance, microlending and savings programs has had little success in improving investments, due to low take-up or to the presence of other larger constraints such as uninsured risk (Banerjee 2013, Karlan et al. 2014) or due to crowding out of investments (de Janvry and Sadoulet 2020). While index insurance can encourage farmers to plant riskier yet more profitable crops and to use more inputs, demand remains low (Kramer et al., 2021). Bundling mutually beneficial agricultural services can potentially address multiple market failures simultaneously and improve technology adoption more effectively. Nonetheless, most studies have focused on relaxing information constraints through advisories and relaxing cash constraints through either cash transfers (Ambler et al. 2020) or increasing access to loans (de Janvry, Sadoulet and Suri 2017). By contrast, and to the best of our knowledge, we are the first study to bundle a smartphone picture-based advisory service, helping relax information constraints, with an indemnity insurance product, in order to transfer agricultural risk.

The paper is structured as follows. In section 2, we introduce the context in which the study was conducted, describe its implementation, and introduce the hypotheses that we aim to test, together with the methods to do so. Section 3 outlines the data used to test these hypotheses. Section 4 presents our findings. We conclude with a discussion of the key take-aways for program design and further research in section 5.

Section 2. Context and Methods

2.1 Background

To measure the effects of providing tailored picture-based agricultural advisories, we implemented a cluster randomized control trial in the states of Punjab and Haryana in northern India during the Rabi (winter) season of 2017-18. Mobile phone prevalence in India has increased exponentially in recent years, in line with rising incomes and mobile technology becoming more affordable. Infrastructure expansion has also resulted in near-universal internet coverage in most parts of the country, unlocking the potential for mobile phones to serve as key platforms for delivering development services to remote rural areas. 40 percent of internet users in India are from rural areas and approximately 97 percent access the internet through their mobile phones (ICEA 2020).

Punjab and Haryana are among the largest rice and wheat producing states in India. Farmers in these states are typically larger and wealthier than the average Indian farmer. Moreover, rural tele-density[1] in these states is higher than in the rest of the country (65 percent in Haryana and 80 percent in Punjab, with 57 percent being the all-India average in 2017; GoI 2018). Such a context allowed for a proof of concept for remote advisories involving an adequate treatment sample, providing the basis for a scalable service to other parts of India.

This study was a follow-up to a project testing the feasibility of picture-based crop insurance (PBI), which uses farmers' smartphone pictures of insured crops to improve the accuracy of claims settlement. An initial study on PBI during the Rabi season of 2016-17 in the states of Punjab and Haryana demonstrated the feasibility of this approach: farmers were willing and able to take usable pictures of their fields; agricultural experts were able to identify severe damage from these pictures; and using these expert assessments in claims settlement reduced the incidence of severe basis events compared to weather index-based insurance and area-yield index-based methods (Ceballos, Kramer, and Robles 2019).[2]

In addition, farmers reported benefiting from the increased field oversight they gained from taking regular pictures, and on-the-ground smartphone pictures enabled remote monitoring of crop phenology, including detection of crop growth stages relative to satellite remote sensing methods (Hufkens et al. 2019). This raised the question of whether the information visible in smartphone pictures could be extended to implement extension, using visual cues from images on growth stage and crop health to tailor preventive and curative advisories to individual farmers. Together with the Centre for Agriculture and Biosciences International (CABI), which was providing generic mobile-based advisories as part of the

[1] Defined as the number of wireline and wireless connections per 100 individuals in the Telecom Statistics India 2018 report by Department of Telecommunications, Govt. of India.
[2] A longer evaluation is currently underway to test the implications of reduced basis risk using smartphone pictures on insurance uptake and impacts.

Direct2Farm extension program (Kansiime et al. 2019) and interested in further tailoring these advisories, we decided to test the feasibility of a picture-based advisories (PBA) approach.

2.2 Intervention

Both PBA and PBI rely on smartphone camera pictures to deliver personalized services. To facilitate collection of these smartphone images from farmers, we developed a dedicated smartphone application, WheatCam, which was available free of charge from the Google Play Store (and is currently available under a more general name, KisanCam, as the project expanded to cover crops beyond wheat). As part of the intervention, farmers were invited to download and register themselves in this app, and they received a short in-person training on how to take valid pictures. Farmers could enroll one of their fields by registering one or more "sites" in the smartphone app, provided that the pictures taken at one site could capture approximately one acre of their field. During the registration process, farmers had to send in an initial geo-tagged and time-stamped picture for each of their registered sites.

The WheatCam app was developed to have in-built features to enable farmers to easily send photographs following a predetermined picture-taking protocol (see Ceballos, Kramer, and Robles 2019). Farmers were asked to take pictures on a regular basis throughout the season, ideally between 10am and 2pm (to keep lighting conditions constant), and always from the same location with the same view angle. To facilitate this, the smartphone app stored the initial picture for each site and used geo-tags to check whether any subsequent pictures for that same site were taken at the same location as the initial picture. When taking a picture, the smartphone screen was showing a line to mark where in the view frame the farmers should keep the horizon, and in the case of a repeat picture, the app provided a "ghost" image (a partially transparent image of the initial picture), allowing the farmer to align static features in the landscape (such as distant trees or structures) with those in the initial picture. After sending in a repeat picture, a farmer was asked to indicate the growth stage of the crop, whether any damage had occurred since the last time the farmer sent in a picture (and if so, what caused the damage), and what inputs had been used. In case a farmer reported damage, he was prompted to take close-up pictures of his crops.

Four local agronomists interpreted the uploaded images, including initial pictures, repeat pictures, and close-up pictures, and sent out personalized advisories based on predetermined cues that were visible in the pictures, along with additional sources of information such as weather data and regional pest monitoring. For this purpose, they used an online platform linked to the smartphone application that allowed them to accept or reject individual farmer's pictures (according to whether the farmer followed the stated picture-taking protocol), review the images for visible cues to prompt specific crop management recommendations, and push remote advisories (PBA messages) directly through the app to each farmer's phone. In addition, at the end of the season, these experts assessed the level of visible damage at each site using the time lapse of pictures. Assessments were made individually, and the median percentage of damage across experts was used as the final damage measure for that site. When large disagreement existed among individual assessments, we used the percentage of damage reached by consensus during a joint review. For farmers with more than 20 percent of assessed visible damage, insured farmers received payments directly into their bank accounts.

2.3 Experimental design

The study was implemented by means of a cluster-randomized trial in which we grouped 203 villages from 5 districts across Haryana and Punjab into 168 clusters of nearby villages.[3] These clusters, in turn, were randomly assigned to one of the following three treatment arms:

1. Control group, where we broadcasted conventional interactive voice response (IVR) and SMS messages (63 villages, grouped into 51 clusters);
2. PBA treatment, where we added personalized, picture-based advisory messages to the broadcasting of conventional generic IVR and SMS messages (69 villages, grouped into 55 clusters); and
3. PBA+PBI treatment, where we provided PBI coverage on top of the IVR, SMS, and PBA messages (71 villages, grouped into 62 clusters).

Thus, farmers in both treatment and control arms received generic weather and crop calendar-based advisory through pre-recorded IVR messages and SMS delivered to their registered mobile phones. Participating farmers in both treatment groups (PBA and PBA+PBI) received in addition personalized advisory, through either the app or SMS, when they submitted a repeat picture or contacted agronomic experts through the app. We randomized treatment at the village level to minimize information spillovers from the advisories and alleviate ethical concerns on varying access to free crop insurance individually.

The sample of villages was drawn from areas in Haryana where our implementing organization for the advisories, CABI, had a prior presence under the Direct2Farm program. In addition, we retained all 50 villages from the pilot study in Haryana and Punjab in the preceding year, which was focused on the feasibility of PBI (see Ceballos, Kramer, and Robles, 2019). Invited farmers in each village were free to choose whether they wanted to participate in the intervention based on messaging marketed through phone calls and local social channels including village meetings and loudspeaker announcements. They could enroll in the services available at their village by contacting program staff who registered farmers on the smartphone application in treatment villages or through a SurveyCTO form in the control villages.

2.4 Research questions and hypotheses

The study was designed to capture outcomes including knowledge and adoption of recommended practices, as well as measures related to the potential future uptake of advisory and insurance including willingness-to-pay and farmer satisfaction with the service. We hypothesize that picture-based advisories (PBA) can potentially have a larger effect on adoption than generic advisories for two reasons. Personalized advisories, by relying on direct visible evidence of a farmer's crop health, may be more relevant and reach farmers in a timelier manner than traditional training visits or other in-person advisory

[3] This sample of 203 villages was drawn from an initial list of 250 potential study villages. Field staff were unable to recruit a sufficient number of farmers in 47 of these 250 potential study villages, which were therefore dropped from the study, resulting in the final set of 203 villages where farmers were registered.

modes. Secondly, if these are perceived as more relevant by the farmer, they may improve knowledge retention. Providing PBA in conjunction with PBI can further improve the potential for adoption.

Our main research questions, then, are the following:

1. Are farmers willing and able to take pictures that can be used to provide personalized remote advisories? Does participation in the program, measured by picture-taking activity differ by treatment arm and between farmers with different demographic characteristics?
2. Does the provision of picture-based advisories improve farmer knowledge of recommended practices? Is the improvement in knowledge due to the medium itself (PBA vs SMS/IVR), the perceived relevance of the advisory, or a difference in content?
3. Does the provision of picture-based advisories improve adoption of recommended practices?
4. What is farmers' willingness-to-pay for picture-based advisories and picture-based insurance?
5. Does providing personalized insurance increase or reduce moral hazard? Does providing advisories have an effect on moral hazard?

Section 3. Data, treatment balance, and empirical strategy

3.1 Administrative data

For our analyses, we use administrative data collected as part of the intervention, as well as primary data collected through a quantitative endline survey. The administrative data includes self-reported data collected through the Wheatcam application both at the time of enrollment and after taking a repeat picture through the course of the season. In treatment villages, interested farmers had to register in the Wheatcam application by sharing basic demographic data, information about their crop, and by taking an initial image of the field they intended to enroll, with the help of program staff. In addition, after taking each repeat picture, a short questionnaire about inputs used and crop damage experienced since the last picture was automatically shown in the app. In control villages, program staff registered farmers for the generic advisories by means of a similar short survey administered through computer-assisted personal interviews (CAPI).

Overall, 3,266 wheat farmers participated in the study, with 1,468 farmers in the control arm and 801 and 997 farmers in, respectively, the PBA and PBA+PBI treatment arms (Table 1). All of these were male, aged between 18 and 88, and 74 percent identified as belonging to an upper or forward, typically landowning, caste (Appendix Table A1). 11 percent of farmers were already relying on their mobile phone to seek agricultural advisory. Appendix Table A2, column A compares basic demographic characteristics of all registered farmers across the three study arms. Control farmers have significantly larger land sizes and are on average 5 years older than treatment farmers. They are also more likely to have lower educational achievement, and less likely to belong to a backward caste and to receive agricultural advisory on their mobile phones. By contrast, farmers in the two treatment groups are not significantly different from one another in terms of farmer characteristics (Appendix Table A1, column B), except for caste: farmers in

PBA+PBI villages are 3 percentage points more likely to identify as a backward caste compared to those in PBA villages.

3.2 Endline survey

In our analyses, we mainly rely on the quantitative endline survey, which was administered at the end of the *Rabi* season in mid-2018. To that end, we randomly selected up to four registered farmers per village who had actively participated in the intervention, using the administrative data as a sampling frame.[4] This resulted in a total sample of 812 farmers from 203 villages with registered farmers (Table 1). The total number of farmers surveyed at endline was lower for two reasons. First, in 13 PBA villages, 7 PBA + PBI villages and 20 control villages, we were unable to locate registered farmers, and thus unable to administer the endline survey. Second, to correct for the self-selection bias between treatment and control, we did not interview the full sample of farmers from control villages, but instead, surveyed a reduced, more comparable sample of farmers who satisfied the following two criteria: (i) owned a smartphone and (ii) would had been interested in registering to receive PBA if it had been offered in their village. Out of 162 farmers approached for the survey in control areas, only 50 farmers (31 percent) from 26 villages met both criteria. Although reducing the effective sample size, this screening process succeeded in providing a more balanced sample as presented in Appendix Table A3 and A4.

The endline survey was administered by program staff using CAPI to measure key outcome variables including farmers' knowledge and adoption of best practices (e.g., input use), damage suffered during the season, and their satisfaction with the insurance product and advisory service. For a subset of 204 participating farmers in Punjab, we also elicited willingness to pay for PBA services alone, PBI insurance alone, and a bundle of PBA and PBI. For each product, farmers were first asked to respond to a dichotomous choice question on whether they were willing to purchase that product at a randomly selected price ranging from INR 200-250 for PBA alone, and from INR 1,000-2,500 for the PBI and PBA+PBI products.[5] When responding positively (negatively), farmers were asked an identical follow-up question using an offer price INR 50 higher (lower) than the initial offer price for PBA alone and INR 500 higher (lower) for PBI alone or the PBA+PBI bundle. Finally, farmers were asked an open-ended question on their maximum willingness to pay for each service or product. We also objectively measured the yields of treatment farmers in the endline sample through standard crop cutting experiments (CCEs).

Table 1: Sample description

	Registered for intervention		Interviewed at endline	
Treatment	**No. of farmers**	**No. of villages**	**No. of farmers**	**No. of villages**

[4] Because of challenges in locating registered farmers, we were unable to administer surveys in 13 PBA villages, 7 PBA + PBI villages, and 20 control villages. Active farmers in treatment villages were considered as those who sent at least one repeat picture in Jan, Feb, and Mar 2018, for those who enrolled in Feb, one pic in Feb and Mar 2018.

[5] We set the initial ranges such that the actual product cost, if offered on a commercial basis, would fall within this range. The cost of providing PBA is significantly lower than the cost of providing PBI, because PBA services do not make any insurance payouts.

Control	1,468	63	50	26
PBA	801	69	160	56
PBA+PBI	997	71	319	64
Total	**3,266**	**203**	**529**	**146**

Note: This figure shows the number of farmers across the 3 treatment arms who registered in the intervention (left) and who completed an endline interview (right), together with the number of villages to which they belonged. The sample for the endline survey consisted of 4 farmers per village chosen randomly from the set of registered farmers who took a minimum of two repeat pictures (in the case of the PBA and PBA+PBI groups) and who owned a smartphone and were interested in registering to receive PBA had it been offered (in the case of the control group).

3.3 Empirical strategy

We estimate the effects of PBA and PBA+PBI services by comparing outcomes between the treatment and control groups using both administrative and survey data. For intermediary outcomes on farmer participation in the treatment, captured using administrative data from the smartphone application, we measure the added effect of PBI by comparing the two treatment groups: PBA vs. PBA+PBI. For final outcomes on knowledge and adoption, captured using survey data from the smartphone application, we measure the effect of PBA by comparing the treatment and control groups: PBA or PBA+PBI vs. control. For all comparisons, we estimate the effect of treatment using ordinary least squares regressions controlling for basic farmer demographic characteristics (age, education, and landholding size). We also account for stratification in the randomization design by controlling for district fixed effects and clustering standard errors by location cluster. To estimate differences in willingness-to-pay for the generic IVR/SMS, PBA, and PBA+PBI services within farmer, we estimate a linear regression of open-ended WTP on the service type controlling for individual fixed effects and the randomly selected dichotomous choice prompt value that immediately preceded the open-ended WTP question in the endline survey. Where appropriate, we provide robustness checks using alternate non-linear regression techniques and using different outcome or covariate measures.

Section 4. Results

We organize the results following the research questions in Section 2.4. We first present findings around farmer participation in the treatment, followed by evidence on primary outcomes related to knowledge and adoption of recommended practices. Next, we discuss findings around willingness-to-pay and moral hazard.

4.1 Participation

To assess the feasibility of providing a picture-based advisory service, we first analyze participation. To that end, Table 2 provides an overview of the number of farmers reached through the different project activities. In total, 1,468 farmers from 63 control villages and 1,798 farmers from 140 treatment villages registered to receive advisories. Of those in the two treatment arms (PBA and PBA+PBI), 76 percent enrolled one site, 18 percent enrolled two sites, and the remaining 6 percent enrolled more than two sites in the dedicated WheatCam app. Farmers sent in a total of 9,608 images, or an average of 5.3 pictures per farmer, of which 88 percent were approved by project staff (meaning that they were of sufficient quality). These approved images were used to provide advisories.

On average, each participating farmer received around one generic advisory message via IVR and slightly less than three generic advisory messages via SMS, covering a range of topics including irrigation, nutrient management, pest and diseases, and weed control. In addition to generic advisories, treatment farmers were provided with PBA messages tailored to the growth stage and any potential issues that agricultural experts detected from the pictures sent in by the farmer.[6] We provided generic messages in both the control and treatment arms to enhance comparability, but as a result, personalized PBA messages are a minority of the messages received. They were, however, personalized to a farmer's situation and sent through a different medium (WheatCam instead of SMS), potentially making these messages stand out.

In total, 1,071 PBA messages were sent to 543 treatment farmers (or 30 percent of all treatment farmers) who sent in at least one repeat picture through the smartphone application. Not all treatment farmers received PBA messages through the app, but since only active farmers were sampled at endline, almost all surveyed farmers (99.2 percent) reported receiving either generic or personalized advisory messages sent as part of the intervention. This means that the endline survey data allow us to evaluate the effects of the advisory service for a sample that has been exposed to this intervention.

Table 2: Implementation overview

	Participation				Advisory activity			
Treatment	No. of farmers registered for advisory service	No. of sites registered in the app	No. of repeat pictures received	No. of valid repeat pictures received	Generic IVR advisories sent	Generic SMS advisories sent	Personalized PBA messages sent	Total no. of advisories sent
Control	1,468	n/a	n/a	n/a	1,141	3,633	n/a	5,063
PBA	801	818	2,365	2,067	502	1,460	445	2,407
PBA+PBI	997	1,275	7,243	6,386	1,347	3,511	626	5,484
Total	**3,266**	**2,093**	**9,608**	**8,453**	**2,990**	**8,604**	**1,071**	**12,954**

Note: Farmers in the control group were not required to register their sites and send in pictures through the smartphone application, and only received generic advisories.

Based on the data presented above, we find that a substantial number of farmers were able to send in repeat pictures of their crops with limited handholding. However, each farmer sent in about 5 pictures per season, indicating substantial room for improvement, which could in turn enable additional

[6] When the expert reviewing the pictures did not find a specific issue in the farmer's field, they sent an advisory message thanking the farmer for sending the picture and stating that no issues were directly visible.

personalized advisories. An important question to consider is thus whether there are any observable characteristics related to the number of pictures sent in by a farmer. We address this question in Table 3, where we present estimates from a linear regression model in which the number of sites registered, the number of repeat pictures, the number of approved repeat pictures, and the average number of valid repeat pictures per site is regressed on a dummy variable for the PBA + PBI treatment, a set of controls, and district fixed effects, with standard errors clustered by randomization unit.

Table 3: Farmer participation in treatment

Covariate	**(1)** No. of sites registered	**(2)** No. of repeat pictures	**(3)** No. of approved repeat pictures	**(4)** Avg. valid repeat pictures per site
PBA+PBI Treatment	0.239***	3.968***	3.509***	1.742***
	(0.047)	(0.660)	(0.610)	(0.368)
Farmer age: 2nd tercile (26-34 years)	0.036	1.242*	1.185**	0.580*
	(0.049)	(0.486)	(0.450)	(0.264)
Farmer age: 3rd tercile (35-88 years)	0.074	2.448**	2.222**	1.414**
	(0.057)	(0.755)	(0.673)	(0.430)
Farmer education: 0-10 years (Primary/Middle school)	0.107	0.324	0.086	-0.342
	(0.096)	(0.563)	(0.520)	(0.347)
Farmer education: >14 years (Higher education)	-0.087	-0.432	-0.391	-0.429
	(0.047)	(0.467)	(0.432)	(0.274)
Total number of acres farmed	0.009	0.045	0.045	0.038*
	(0.008)	(0.033)	(0.032)	(0.018)
Number of observations	1798	1798	1798	1798
R-squared	0.098	0.173	0.168	0.166

Standard errors in parentheses and clustered by unit of randomization (cluster). ***, **, and * indicate significance at the 1, 5, and 10 percent critical level. Coefficients for district fixed effects and intercept hidden for readability

Across all four outcome variables, farmer participation was higher when the advisory was bundled with a free insurance policy instead of being offered as a stand-alone service. This could be related to farmers having a financial interest in sending in images, as active participation was a requirement receiving future insurance payouts. Moreover, after controlling for age, education, and wealth, farmers in the PBA+PBI arm registered an additional 0.24 sites and sent nearly 4 pictures more on average than farmers in the PBA arm. While we would have expected younger, more educated, and wealthier farmers to participate relatively more, this is not what we found. Older farmers (26 years and above, and especially those who were 35 years and above) were more active compared to younger farmers (18-25 years of age). In a robustness check (available upon request), we find that this result holds in both the PBA only and the PBA + PBI treatment arm, indicating that it is not the financial incentive provided by insurance that encourages older farmers to participate more. Finally, education and wealth were not associated with an increase in participation, suggesting that the intervention is not further aggravating a digital divide.

Given the increased participation from farmers who were randomly selected to receive not only PBA but also picture-based insurance, we aim to identify patterns in take-up of insurance in Table 4. Although insurance was provided free of charge, universal enrollment would not be expected because farmers were required to provide several documents, introducing a behavioral cost that farmers would only want to incur if they valued the insurance product sufficiently. In PBI villages, 472 out of 997 registered farmers (47 percent) enrolled in insurance by submitting necessary documents to the insurance underwriter, with the vast majority (43 percent) enrolling one or two acres each, and a smaller number of farmers (4 percent) enrolling larger areas, up to a maximum of seven acres.

Table 4: Farmer participation in insurance

	(1)	**(2)**
Variable	**Insured**	**Insured area**
Farmer age: 2nd tercile 26-34 years	0.186***	-0.020
	(0.036)	(0.086)
Farmer age: 3rd tercile 35-88 years	0.280***	0.189*
	(0.052)	(0.080)
Farmer education: 0-10 years (Primary/Middle school)	-0.088*	-0.037
	(0.037)	(0.104)
Farmer education: >14 years (Higher education)	-0.041	0.032
	(0.035)	(0.076)
Total number of acres farmed	0.003	0.001
	(0.003)	(0.003)
Number of observations	997	472
R-squared	0.127	0.118

Standard errors in parentheses and clustered by unit of randomization (cluster). ***, **, and * indicate significance at the 1, 5, and 10 percent critical level. Coefficients for district fixed effects and intercept hidden for readability.

Table 4 shows that insurance enrollment was significantly higher among older farmers compared to farmers aged 18-25 years. Although these farmers also submitted more images (Table 3), in robustness checks, we observed this increase in both the PBA only and the PBA + PBI treatment arm, suggesting that it is not the financial incentive provided by insurance that increased participation among older farmers. Perhaps these farmers were more interested in the picture-based methodology, and therefore both submitted more pictures, and enrolled in insurance more often. In Table 4, we also find lower enrollment among farmers with fewer years of schooling, although the coefficient is statistically significant only at the 10 percent level. Interestingly, larger farms are not more likely to be insured. Finally, among those who choose to take up insurance, we do not find major differences in the number of insured acres in terms of farmer's age and education, or farm size; the insured area was higher among the oldest tercile of farmers, but this difference is statistically significant only at the 10 percent level.

In sum, we find that farmers are able and willing to send in images in order to receive personalized advisories, though adding a financial incentive for doing so (i.e., providing a free-of-cost insurance policy) significantly increases participation. Participation, both in terms of taking regular pictures and enrolling in insurance, is higher among relatively older farmers, and not correlated with education or farm size, suggesting that this digital innovation is not exacerbating existing inequities in access to digital technologies across generations or between more versus less educated and wealthy farmers. These findings speak to the feasibility of providing picture-based advisories as an inclusive ICT-based innovation to improve knowledge and behavior, which can be boosted by bundling them with a value-added service such as insurance. We return to complementarities between advisories and insurance below.

4.2 Knowledge

We evaluated farmers' knowledge of practices through a set of five questions, for which the answers could be coded as either correct or incorrect (Appendix A5). Using these measures, we create an ordinal knowledge score ranging from 0 (only incorrect answers) to 5 (only correct answers) for each farmer. All five questions pertained to content that was disseminated as part of the PBA service in treatment villages. We also construct an indicator for 'common topics' that were covered in both the personalized PBA and generic IVR / SMS messages. This score ranges from 0 to 3 as it is based on only three of the five knowledge questions. In Table 5, we compare scores obtained for these indicators in the control group versus the two treatment arms.

On average, farmers in the control group obtained poor knowledge scores, scoring 12.8 percent on the full knowledge test, 16.7 percent when including only the three questions around topics covered in both the generic IVR/SMS and PBA messages, and 7 percent when focusing on the two questions for which answers were provided only through PBA messages. Treatment farmers (who received both personalized PBA and generic IVR/SMS messages) scored approximately 10 percentage points higher than control farmers, representing an increase of 78 percent in average knowledge scores.

Interestingly, treatment farmers score higher than control farmers even when focusing on the subset of topics disseminated both through PBA and generic IVR/SMS. These differences remain significant despite controlling for total number of advisory messages, age, education, and landholding size (Table 5).[7] This suggests that farmers incorporate content better through the PBA approach even when this content does not differ from what is provided through the generic IVR messages. Although we did not formally test this channel, farmers may pay more attention to PBA content perhaps due to the perception that PBA is personalized and more relevant to them.

Table 5: Farmer knowledge score at endline

	Control		Treated		Difference
Knowledge score (% correct answers)	**N**	**Mean/SE**	**N**	**Mean/SE**	**C vs T**
Total (5 questions)	50	0.128 [0.024]	479	0.228 [0.015]	-0.100***
Common topics (3 questions)	50	0.167 [0.034]	479	0.273 [0.016]	-0.106**
PBA topics alone (2 questions)	50	0.070 [0.030]	479	0.162 [0.025]	-0.092***

Standard errors, clustered by unit of randomization, are in parentheses. The value displayed for t-tests are the differences in the means across the groups. C vs T tests for difference in means between control farmers and treatment farmers (PBA/PBI). ***, **, and * indicate significance at the 1, 5, and 10 percent critical level, respectively, when controlling for age, education, landholding size, number of advisory messages received, and district fixed effects.

4.3 Adoption

An important follow-up question is whether PBA, improving farmers' knowledge of recommended technologies and practices, leads to behavioral change, reduced risk exposure, and improved productivity. Table 6 compares the use of recommended inputs at some point during the season (as a proxy for technology adoption), the incidence of damage (to capture risk exposure), and self-reported yields (productivity) between treatment and control farmers. Consistent with other studies on the impacts of agricultural advisory services (Aker, Gosh, and Burrell 2016, Fabregas, Kramer and Schilbach 2019), despite a positive effect of advisories on knowledge, farmers do not appear to put this knowledge into action. At endline, we find no significant differences between farmers in treatment and control areas in terms of technology adoption, based on our indicators around use of recommended herbicides, pesticides, and fungicides. Treatment farmers reported higher instances of damage than control farmers, but this was statistically significant only for pests and diseases, reported by a small minority of farmers

[7] Because knowledge scores are ordinal variables, we also estimate an ordered logit model. Results based on this model, available upon request, are qualitatively similar.

(5.8 percent in the treatment group and none in the control group). The majority of farmers only reported weather-related damage (63 percent in treatment and 44 percent in control), which is an exogenous factor unaffected by treatment. Finally, self-reported yields do not significantly differ between treatment and control farmers.

Table 6: Farmer self-reported input use, damage and yields at endline

	Control		Treated		Difference
Variable	**N**	**Mean/SE**	**N**	**Mean/SE**	**C vs T**
Used recommended herbicide	50	0.980	479	0.873	0.107
		[0.020]		[0.015]	
Used recommended pest/fungicide	50	0.200	479	0.242	-0.042
		[0.057]		[0.020]	
Reported damage from pest and disease	50	0.000	479	0.058	-0.058*
		[0.000]		[0.011]	
Reported damage from weather	50	0.440	479	0.635	-0.195
		[0.071]		[0.022]	
Reported any damage	50	0.480	479	0.662	-0.182
		[0.071]		[0.022]	
Self-reported yield (in Quintals Per Acre)	43	20.523	456	18.661	1.862
		[0.572]		[0.191]	

Controls for age, education, landholding size, number of advisory messages and district fixed effects. Standard errors in parentheses and clustered by unit of randomization (cluster). The value displayed for t-tests are the differences in the means across the groups. C vs T tests for difference in means between control farmers and treatment farmers (PBA/PBI). ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

It is possible that PBA messages do not influence the overall use of inputs throughout the season but do influence the timing of their application. This could be due to personalized advisories being more relevant or timely than generic ones (since two neighboring farmers may plant the same crop in different dates) or from the visible information in pictures allowing experts to identify certain symptoms sooner than the farmer would be able to. To explore farmers' responsiveness to the PBA intervention more accurately, we relate the timing and nature of both personalized and generic advisories received by farmers to the timing of input application and other relevant practices. To do this, we draw on responses to an endline module inquiring about the number of times and rough timing (first, second, or third decal of a given calendar month) that the farmer irrigated or applied different inputs in their field. Using these responses, we construct a dataset matching reports of input use and practices to any advisory disseminated in a certain window prior to the date of reporting.

In Table 7, we present OLS estimates of input use reports on advisories received in a window of 15 days previous to the date of the report. Input use reports and generic and personalized advisory messages were both classified into 4 categories – weeding or applying weedicide, applying any type of fertilizer, applying irrigation, and applying pesticide or fungicide. For each input use category, we estimate two specifications modelling a dummy taking a value of 1 if input use was reported and 0 otherwise as dependent variable: considering a single dummy capturing whether a generic or personalized advisory message was sent encouraging the farmer to apply that input alone or considering the whole array of dummies on different categories, in order to identify potential complementarities between categories or other confounding effects. All models include fixed effects at the farmer level and time dummies for each decal of the season (to control for the normal timing of application for certain inputs such as irrigation or fertilizer). Estimates considering a window of 30 days prior to the date of reporting are presented in Appendix A5 as a robustness check.

Overall, we do not find strong evidence of changes in the timing of input use in response to receiving generic or personalized advice. The few significant coefficients in Table 7 indicate reduced input use in response to receiving advice to apply other types of inputs and may reflect spurious correlations stemming from multiple hypothesis testing.

Now, it is possible that farmers' self-reported data at endline on input use throughout the season are affected by recall bias. As an alternative to the analyses presented above, we draw on the higher frequency administrative data available from farmers' responses to questions in the Wheatcam smartphone application. Each time a farmer sent a repeat picture of his field, he also answered a short questionnaire on the inputs he had applied since the previous repeat picture. Since the number of observations may vary by farmer according to their level of activity in the smartphone application, we weight the observations by the inverse of the number of repeat pictures sent in, to provide higher weights to farmers with fewer repeat pictures and ensure all farmers are represented equally in the analyses. When following this approach, the null results reported in Table 7 persist, arguably due to the fact that these data tend to be much noisier than the one captured at endline.

Table 7: Self-reported input use and advisories received

Variable	(1) Applied Weedicide	(2) Applied Weedicide	(3) Applied Nutrient	(4) Applied Nutrient	(5) Irrigated field	(6) Irrigated field	(7) Applied Pest/Fungicide	(8) Applied Pest/Fungicide
Weedicide advice (SMS/IVR)	0.0341	0.0497		0.0323		0.0126		-0.0536***
	(0.0383)	(0.0407)		(0.0349)		(0.0455)		(0.0177)
Nutrient advice (SMS/IVR)		-0.0952*	0.0656	0.0451		0.0365		0.0230
		(0.0481)	(0.0466)	(0.0555)		(0.0651)		(0.0383)
Irrigation advice (SMS/IVR)		0.0584		0.00514	0.0172	-0.0107		0.00808
		(0.0686)		(0.0897)	(0.0678)	(0.0863)		(0.0479)
Pest/Fungicide advice		0.0199		0.0881		-0.0272	0.0106	0.0141
(SMS/IVR)		(0.0463)		(0.0594)		(0.0577)	(0.0526)	(0.0517)
Weedicide advice (PBA)	-0.0193	0.000737		0.0573		-0.0165		0.0478
	(0.0393)	(0.0404)		(0.0443)		(0.0485)		(0.0322)
Nutrient advice (PBA)		-0.0251	0.0102	-0.00271		-0.0555		0.0447
		(0.0562)	(0.0603)	(0.0610)		(0.0484)		(0.0446)
Irrigation advice (PBA)		-0.161**		-0.234*	-0.0478	-0.0727		-0.147
		(0.0707)		(0.140)	(0.174)	(0.178)		(0.183)
Pest/Fungicide advice (PBA)		0.141		-0.0384		0.112	0.163	0.164
		(0.147)		(0.116)		(0.114)	(0.178)	(0.181)
Number of observations	2,778	2,778	2,778	2,778	2,778	2,778	2,778	2,778
R-squared	0.267	0.270	0.349	0.351	0.255	0.256	0.293	0.297

Notes: Robust standard errors in parentheses. Coefficients for week-wise time dummies and intercept hidden for readability. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level, respectively.

4.4. Farmers' risk exposure and asymmetric information

A major concern for insurers is their clients' risk exposure, as it directly determines expected payouts and thus the costs of providing insurance. Reducing farmers' risk exposure, and the uncertainty around expected payouts introduced by asymmetric information, can increase the sustainability of insurance. Traditional indemnity-based crop insurance is often plagued by two problems stemming from information asymmetry: adverse selection, or the tendency of farmers with worse prospects being more likely to select into insurance, increasing risk exposure *ex ante*; and moral hazard, or the incentives for insured farmers to put in lower effort or invest sub-optimally during crop growth, with the objective to maximize their chance to receive a payout, resulting in increased risk exposure *ex post*.

Providing PBA may serve to reduce the probability of information asymmetry issues arising from the indemnity nature of the PBI product in various ways. First, receiving more accurate advisory can help farmers better minimize risk by taking appropriate preventive or curative actions to reduce yield loss, thereby reducing the cost of preventive action and reducing moral hazard. Second, receiving personalized advisory directly related to the regular pictures taken in their field, farmers may have an increased perception of being monitored by the insurance company thereby disincentivizing them to adversely select into the program or commit moral hazard. Third, when farmers select into insurance not only to access insurance but also to access advisories, the insurance policy may attract not only farmers with an increased risk profile, but also low-risk farmers who are motivated to adopt good practices and technologies.

Table 8: Farmer perception on advisories

	(1)	(2)	(3)	(4)
	Helped minimize risk	**Was tailored to farmer**	**Helped minimize risk**	**Was tailored to farmer**
Advisory received from intervention	0.076***	0.096***	0.117**	0.085**
	(0.022)	(0.019)	(0.037)	(0.033)
Advisory received from intervention # PBI			-0.066	0.017
			(0.045)	(0.041)
Constant	0.785***	0.888***	0.785***	0.888***
	(0.011)	(0.010)	(0.011)	(0.010)
Observations	502	502	502	502
R-squared	0.046	0.088	0.055	0.089

To understand the direction of behavioral change towards or away from opportunistic behavior, we first study farmer's own perception of the program. Table 8 presents a comparison of these perceptions controlling for farmer fixed effects and treatment status. Most farmers reported benefiting from advisories in some way. However, treatment farmers were significantly more likely to perceive advisories received in response to pictures as helping them minimize risk and as being tailored to their context compared to other advisory sources utilized during the study period. There was no difference in these perceptions between PBA treatment and PBA+PBI treatment farmers. This suggests that PBA has the potential to disincentivize moral hazard by reducing risk and improving monitoring.

Table 9: Evidence on asymmetric information concerns

	Uninsured		Insured		Difference	
Variable	**N**	**Mean/SE**	**N**	**Mean/SE**	**Insured vs Non-insured**	**PBA vs PBA+PBI**
Reported damage from pest and disease	228	0.031	251	0.084	-0.053	-0.050
		[0.011]		[0.018]		
Reported damage from weather	228	0.583	251	0.681	-0.098**	-0.033
		[0.033]		[0.029]		
Reported any damage	228	0.601	251	0.717	-0.116***	-0.065
		[0.033]		[0.028]		
Self-reported yield (in Quintals Per Acre)	217	19.748	239	17.67	2.074***	1.852***
		[0.234]		[0.281]		
CCE yield (in Quintals Per Acre)	166	19.251	264	19.29	-0.040	-0.433
		[0.372]		[0.276]		
Detected damage from pictures (%)	148	1.811	283	3.982	-2.172	-2.453**
		[0.519]		[0.820]		

Controlled for district fixed effects, age, education and land size. Standard errors in parenthesis clustered by unit of randomization. The value displayed for t-tests are the differences in the means across the groups. C vs T tests for difference in means between control farmers and treatment farmers (PBA/PBI). ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

To test for the presence of adverse selection and moral hazard, a final analysis compares outcomes for insured farmers with those for non-insured farmers from the same set of PBA+PBI treatment villages, where advisories were combined with PBI. We control for village fixed effects, in order to focus on differences between insured and uninsured farmers within villages, thus combining the effects of adverse selection and moral hazard into one estimate. Table 9 presents the results. We find that insured farmers are more likely to report damage to their crops, especially damage due to adverse weather conditions, and that they report on average lower yields than non-insured farmers. While this finding could reflect the presence of adverse selection or moral hazard, it could also be due to a tendency to over-report damage or under-report yields in the hope to trigger insurance payouts. In contrast, more objective yield measures, collected by means of crop cutting experiments, and expert assessments of damage visible in the submitted smartphone pictures, show no significant differences between the insured and non-insured. This evidence allows to conclude that, at least in the context of this study, bundling PBI with personalized remote advisories (PBA) does not seem to induce substantial adverse selection or moral hazard.

4.5 Willingness to pay

As described above, the endline survey included a module eliciting willingness to pay (WTP) for PBA, PBI, and a bundle of PBA and PBI. These consisted of a dichotomous choice question (with answer options being "yes" or "no") in which the farmer was asked whether he was willing to purchase each product if it were offered for INR X, whereby X was a randomly selected offer price. For the range of predefined offer prices, responses to this question were negative ("no") for all but six farmers, meaning that most participants were not willing to pay moderately discounted commercial rates for any of the three products (PBA only, PBI only, or PBA + PBI). We therefore rely on the responses to the open-ended WTP question for our analysis, which exhibit a higher degree of variation. Still, open-ended WTP was quite low for most farmers. In the case of PBA alone, only four farmers were willing to pay a strictly positive price, but average WTP was higher for PBI alone, at INR 223 (54 percent with a strictly positive WTP), and for PBA+PBI, at INR 351 (72 percent with a WTP greater than zero).

A within-subject comparison of WTP across the three products is presented in Table 10, in which we estimate a model that regresses willingness to pay on dummy variables indicating the PBI only and PBI + PBA products (using PBA only as the reference category), and a set of control variables. As mentioned, although the willingness to pay for the advisory service when offered as a stand-alone service is virtually zero, respondents are willing to pay significantly more than zero for the PBI product, and even more when advisories are added to the insurance product (PBA+PBI). The WTP for the three services is not associated with the randomly determined, initial offer price in the dichotomous choice question (second column), or with key demographic characteristics of farmers when estimating the model without fixed effects (results available upon request).

As a robustness check, in the third column, we present a linear mixed effects model to account for both covariance within subjects (correlation in error terms across different choices) and between subjects (correlation in error terms across respondents from the same cluster of villages). The coefficients for PBI and PBA+PBI remain significant, and the WTP for the bundled product remains significantly larger than that for PBI when offered as a stand-alone product. Overall, we find robust evidence that the WTP for a bundled product is higher than the WTP for insurance and advisories when offered as stand-alone services, indicating that farmers perceive value in receiving these products as a bundle.

Table 10: Farmer willingness to pay

Variable	(1) WTP (Open-ended, INR)	(2) WTP (Open-ended, INR)	(3) WTP - Mixed Effects (Open-ended, INR)
PBI only	219.4***	177. 0**	157.2**
	(15.52)	(66.20)	(51.92)

PBI+PBA	347.3***	232.4**	
	(18.52)	(70.67)	213.1***
Initial offer		0.178	(59.73)
		(0.226)	
Initial offer * PBI		-0.135	0.130
		(0.230)	(0.115)
Initial offer * PBA+PBI		-0.095	-0.080
		(0.229)	(0.122)
Constant	3.676	-27.31	-34.08
	(8.849)	(40.00)	(59.76)
Observations	612	612	612
R-squared	0.345	0.366	

Standard errors in parentheses and clustered by farmer. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level, respectively. Coefficients for individual and cluster fixed effects and intercept hidden for readability.

Conclusion

This study describes the results from a cluster randomized controlled trial to test the effectiveness of tailored picture-based agricultural advisories (PBA) in the states of Punjab and Haryana, northern India, during the Rabi (winter) season of 2017-18. The intervention was built over an existing trial around picture-based insurance (PBI), a novel damage assessment approach that relies on a stream of pictures of farmers' fields to validate insurance claims and trigger payouts. By reviewing pictures sent by farmers of their own fields, agronomic experts were able to monitor regular crop growth or identify potential issues and send back personalized advice, either responsive or preventive, via a text or audio message. The study was comprised of a control arm that received generic advisories via SMS or IVR and two treatment arms: one where farmers received PBA advisories in addition to generic ones, and another one where farmers received a free PBI insurance product on top of generic and PBA advisories.

We find positive participation rates, with a substantial number of farmers willing and able to send in repeat pictures of their crops with limited handholding in order to access the personalized advisory service. While older farmers were more active compared to younger ones, we observe no differential participation related to education or wealth, suggesting that the intervention is not further aggravating existing digital divides.[8] The PBA intervention is associated with moderate increases in knowledge, even on topics that were covered through both generic and personalized advisory modes. However, the increases in knowledge do not translate to increased adoption of recommended practices or inputs, either in terms of the probability of applying recommended inputs or practices at some point during the season or in the timing of application, as informed by high-frequency data collected throughout the season.

Whilst contradicting findings from Cole and Fernando (2021) that advisories change practices without affecting knowledge, these findings are in line with those in other studies (Aker, Gosh, and Burrell 2016, Fabregas, Kremer, & Schilbach 2019) who find increased knowledge from advisories delivered digitally but no effects on adoption or productivity. Estimating such effects is nevertheless challenging. Advisories can have an ambiguous effect on input use, for instance inducing substitution within a given input category, or encouraging reduced use of chemical pesticides or herbicides for some farmers and increased use for others, depending on their baseline levels of use. Advisories of a preventive nature, in addition, may also lead to reduced input use over time as crops become healthier and less susceptible to damage. More detailed and longer-term data may thus be required to estimate the impact of advisories on adoption.

Our findings also speak to the presence of synergies between advisories and insurance. Farmer engagement, as measured by the number of sites created and the number of repeat pictures taken throughout the season, was found to be stronger when PBA was bundled with a free insurance policy instead of being offered as a stand-alone service. WTP was also higher for PBA when offered jointly with insurance. Finally, farmers reported that advisories helped them minimize risk, indicating that PBA could provide cost-savings to insurance companies by reducing the frequency or level of agricultural losses.

[8] In other settings, where smartphone ownership is significantly lower, this finding could be different, but could be overcome by working through champion farmers trained to send in images on behalf of other farmers in their communities.

Unfortunately, in the absence of a PBI only treatment arm, our research design does not allow us to formally test this channel by, for instance, comparing different damage and yield measures with those observed when bundling PBI with PBA. Even though such a mechanism would not be expected to be strong in the absence of impact of PBA on adoption of recommended practices, this remains as an important topic for future research.

A limitation of the picture-based advisory approach implemented as part of this study is that it relies on manual processing of images and inspection of farmers' images by agricultural experts. In the small scale of this pilot, this was feasible, but in order to scale a service of this nature, one would need to automate image assessment. Ongoing work is focused on this objective. For instance, Hufkens et al. (2019) describe a workflow to prepare images for analysis, and to subsequently extract greenness indices, which they show are more informative of the onset of crucial crop growth stage compared to vegetation indices derived from satellite imagery. Follow-up work is showing that growth stages and different types of crop damage, for instance due to fertilizer shortages or weeding practices, can also be identified directly from the images with high accuracy using machine learning. This could help tailor advisories to the growth stage that is visible in images submitted by the farmer, or to any crop damage that machine learning algorithms may detect, in order to increase the relevance and timeliness of any recommendations sent to the farmer.

In conclusion, this paper provides a proof of concept for personalized remote advisories provided on the basis of smartphone images submitted by farmers themselves. This interactive approach could be a strategy to increase knowledge of good agricultural practices and technologies, and if bundled with insurance, increase farmers' willingness to pay for insurance, whilst reducing farmers' risk exposure, thus offering a potential mechanism to lower insurance premiums. Although longer-term impact evaluations around this approach are needed to shed light on the question whether this approach can indeed enhance technology adoption, providing extension agents with eyes on the ground through the smartphone images appears to be a promising strategy to increase the reach, relevance, and timeliness of extension and advisory systems.

Appendix

Table A1. Descriptive statistics

	N	Mean	SD	Data source
Covariates				
Age in years (as of June 2018)	3266	34.179	12.497	All participating farmers
Total number of acres farmed	3266	6.164	7.222	All participating farmers
Farmer education: 10-14 years/High school	3266	0.575	0.494	All participating farmers
Farmer education: 0-10 years/up to Middle school	3266	0.257	0.437	All participating farmers
Farmer education: 14+ years/Higher education"=	3266	0.168	0.374	All participating farmers
Does not identify as forward caste	3266	0.257	0.437	All participating farmers
Uses mobile phone to seek agricultural advisory	3266	0.108	0.311	All participating farmers
Outcomes				
No. of sites registered in Wheatcam application	1798	1.164	0.868	Participating farmers in Treatment
No. of repeat pictures sent in Wheatcam application	1798	5.344	9.610	Participating farmers in Treatment
No. of approved repeat pictures send in Wheatcam application	1798	4.701	8.673	Participating farmers in Treatment
Average repeat pictures sent per site	1798	3.237	5.252	Participating farmers in Treatment
Knowledge score (0-5)	529	1.095	0.910	Surveyed at endline
Use recommended herbicide	529	0.883	0.322	Surveyed at endline
Used recommended pesticide	529	0.238	0.426	Surveyed at endline
Reported damage from pest or disease	529	0.053	0.224	Surveyed at endline
Reported damage from weather-related causes	529	0.616	0.487	Surveyed at endline
Reported any damage to wheat crop	529	0.645	0.479	Surveyed at endline
Yield : Self-reported (in quintals per acre)	499	18.822	4.082	Surveyed at endline
Yield : CCE (in quintals per acre)	430	19.275	4.603	Subsample of surveyed at endline

Table A2: Balance table – All participating farmers

Variable	Control N	Control Mean/SE	PBA N	PBA Mean/SE	PBI N	PBI Mean/SE	Difference C vs T^	Difference PBA vs PBI^^
No. of acres farmed	1468	6.989	801	5.343	997	5.608	1.499***	-0.265
		[0.423]		[0.594]		[0.457]		
Main occupation is agriculture	1468	0.927	801	0.984	997	0.974	-0.051***	0.010
		[0.015]		[0.005]		[0.006]		
Farmer age	1468	37.114	801	31.431	997	32.063	5.333***	-0.632
		[0.935]		[0.681]		[0.530]		
Farmer education: 10-14 years (High school)	1468	0.524	801	0.623	997	0.611	-0.092***	0.012
		[0.027]		[0.027]		[0.026]		
Farmer education: 0-10 years (Primary/Middle school)	1468	0.392	801	0.141	997	0.150	0.246***	-0.009
		[0.030]		[0.019]		[0.016]		
Farmer education: >14 years (Higher education)	1468	0.084	801	0.236	997	0.239	-0.154***	-0.003
		[0.013]		[0.023]		[0.020]		
Does not identify as forward caste	1468	0.217	801	0.270	997	0.305	-0.072*	-0.035
		[0.040]		[0.072]		[0.045]		
Used mobile phone often to receive advisories	1466	0.528	801	0.396	997	0.178	0.253***	0.218***
		[0.052]		[0.061]		[0.033]		

Controls for district fixed effects. Standard errors in parentheses clustered by unit of randomization (cluster). The value displayed for t-tests are the differences in the means across the groups. C vs T tests for difference in means between control farmers and treatment farmers (PBA/PBI). PBA vs PBI compares means between farmers in the two treatment groups. *, **, and * indicate significance at the 1, 5, and 10 percent critical level.**

Table A3: Balance table - Endline sample

Variable	Control N	Control Mean/SE	PBA N	PBA Mean/SE	PBI N	PBI Mean/SE	Difference C vs T^	Difference PBA vs PBI^^
No. of acres farmed	50	4.680	160	8.744	319	6.602	-2.637**	2.142
		[0.476]		[0.753]		[0.369]		
Main occupation is agriculture	50	0.880	160	0.994	319	0.969	-0.097***	0.025
		[0.046]		[0.006]		[0.010]		
Farmer age	50	36.040	160	34.188	319	34.972	1.330	-0.784
		[2.272]		[0.858]		[0.635]		
Farmer education: 10-14 years (High school)	50	0.560	160	0.588	319	0.592	-0.031	-0.005
		[0.071]		[0.039]		[0.028]		
Farmer education: 0-10 years (Primary/Middle school)	50	0.240	160	0.181	319	0.179	0.060	0.003
		[0.061]		[0.031]		[0.021]		
Farmer education: >14 years (Higher education)	50	0.200	160	0.231	319	0.229	-0.030	0.002
		[0.057]		[0.033]		[0.024]		
Does not identify as forward caste	50	0.160	160	0.125	319	0.248	-0.047	-0.123***
		[0.052]		[0.026]		[0.024]		
Used mobile phone often to receive advisories	50	0.5	160	0.537	319	0.245	0.158***	0.293
		[0.071]		[0.040]		[0.024]		

Controls for district fixed effects. Standard errors in parentheses clustered by unit of randomization (cluster). The value displayed for t-tests are the differences in the means across the groups. C vs T tests for difference in means between control farmers and treatment farmers (PBA/PBI). PBA vs PBI compares means between farmers in the two treatment groups. *, **, and * indicate significance at the 1, 5, and 10 percent critical level.**

Table A4: Control farmers - Comparison between the full sample and comparative sample

Variable	Control - All other		Control - Endline interviewed		Difference
	N	Mean/SE	N	Mean/SE	Full vs Comparative
No. of acres farmed	1418	7.070	50	4.680	2.390***
		[0.440]		[0.468]	
Main occupation is agriculture	1418	0.929	50	0.880	0.049
		[0.016]		[0.045]	
Farmer age	1418	37.152	50	36.040	1.112
		[0.955]		[2.400]	
Farmer education: 10-14 years (High school)	1418	0.523	50	0.560	-0.037
		[0.029]		[0.062]	
Farmer education: 0-10 years (Primary/Middle school)	1418	0.398	50	0.240	0.158***
		[0.031]		[0.051]	
Farmer education: >14 years (Higher education)	1418	0.080	50	0.200	-0.120*
		[0.013]		[0.054]	
Does not identify as forward caste	1418	0.219	50	0.160	0.059
		[0.042]		[0.041]	
Used mobile phone often to receive advisories	1416	0.529	50	0.500	0.029
		[0.053]		[0.074]	

Controls for district fixed effects. Standard errors in parentheses clustered by unit of randomization (cluster). The value displayed for t-tests are the differences in the means across the groups. C vs T tests for difference in means between control farmers and treatment farmers (PBA/PBI). PBA vs PBI compares means between farmers in the two treatment groups. *, **, and * indicate significance at the 1, 5, and 10 percent critical level.**

Appendix A5. Knowledge Questions administered at endline

1. What weedicide can you apply if you see this weed in your field? (based on content disseminated through PBA and generic IVR/SMS)

a) Phenoxodyn or Phenoxypropyethyl (Axil or Puma Power)
b) Metsulfuran and Iodosulfuran
c) Metsulfuran and Sulfosulfuran (Total)
d) Accord Plus
e) Metribuzin
f) 2,4-D (Kill Out)
g) Glyphosate (Roundup)
h) Other
i) Do not know

Correct answer: (e) and (f)

2. What weedicide can you apply if your weeds are not destroyed even after application of 2,4-D? (based on content disseminated through PBA and generic IVR/SMS)

a) Algrip
b) Affinity
c) Metribuzin
d) Glyphosate (Roundup)
e) Other
f) Do not know

Correct answer: (b)

3. What is the recommended harvesting method if there is rain before harvest and your crops are moist? (based on content disseminated through PBA and generic IVR/SMS)

a) Use combine harvester
b) Harvest by hand
c) Other
d) Do not know

Correct answer: (b)

4. If your land is saline, what wheat seed variety can you use to better your yields? (based on content disseminated through PBA only)

a) KRL-210
b) HD2967
c) WH1105
d) PBW550
e) Other
f) Do not know

Correct answer: (a)

5. If you can irrigate your field 3 times in the season, which are the appropriate stages for irrigation? (based on content disseminated through PBA only)

a) Crown root, heading, milking
b) Crown root, tillering, Anthesis/flowering
c) Tillering, Anthesis/flowering, milking
d) Booting, Anthesis/flowering, milking
e) Other
f) Do not know

Correct answer: (a)

Table A6. Adoption - Robustness check using 30-day window between advisory and input use

VARIABLES	(1) Applied Weedicide	(2) Applied Weedicide	(3) Applied Nutrient	(4) Applied Nutrient	(5) Irrigated field	(6) Irrigated field	(7) Applied Pest/Fungicide	(8) Applied Pest/Fungicide
Weedicide advice (SMS/IVR)	0.0261	0.0412		0.0214		0.00751		-0.0168
	(0.0344)	(0.0372)		(0.0306)		(0.0389)		(0.0255)
Nutrient advice (SMS/IVR)		-0.0701	0.0176	-0.0219		0.0755		0.0266
		(0.0449)	(0.0445)	(0.0475)		(0.0587)		(0.0378)
Irrigation advice (SMS/IVR)		0.0356		0.0833	0.0491	0.00676		-0.0126
		(0.0496)		(0.0627)	(0.0483)	(0.0582)		(0.0406)
Pest/Fungicide advice (SMS/IVR)		0.0251		0.0753		-0.0562	0.00105	0.00467
		(0.0407)		(0.0482)		(0.0488)	(0.0507)	(0.0508)
Weedicide advice (PBA)	-0.0188	-0.00499		0.0563		-0.0389		0.0287
	(0.0337)	(0.0341)		(0.0346)		(0.0459)		(0.0258)
Nutrient advice (PBA)		-0.0367	0.0223	0.00791		-0.0406		-0.00246
		(0.0416)	(0.0432)	(0.0433)		(0.0496)		(0.0425)
Irrigation advice (PBA)		-0.180**		-0.201	-0.0410	-0.0896		-0.190
		(0.0872)		(0.152)	(0.176)	(0.211)		(0.173)
Pest/Fungicide advice (PBA)		0.102		-0.0783		0.134*	0.155	0.162
		(0.117)		(0.0990)		(0.0800)	(0.135)	(0.140)
Observations	2,778	2,778	2,778	2,778	2,778	2,778	2,778	2,778
R-squared	0.267	0.269	0.348	0.351	0.255	0.257	0.293	0.294

Robust standard errors in parentheses. Coefficients for week-wise time dummies and intercept hidden for readability. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

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