Customized Agricultural Advisory Services for Smallholder Farmers in India*

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March 26, 2025

Abstract

Precision Development (PxD) has collaborated with governments and other partners to design and scale mobile phone-based agricultural information services among millions of farmers in India. In this report, we analyze PxD's administrative data across five states and survey data from a randomized evaluation in Odisha to understand how service usage and the impact of digital advisory vary by farmer characteristics. Specifically, we focus on disadvantaged groups, including women, poorer farmers, farmers with low education levels, farmers with low productivity levels, and farmers in less-serviced areas. Our analysis generates three key findings. First, the majority of farmers who register for the service successfully access agricultural information and continue to use the service across multiple seasons, but the intensity of service usage is often lower among the disadvantaged groups. Second, the randomized evaluation of the service among rice farmers in Odisha offers evidence that a mobile phone-based advisory service can help farmers cope with weather shocks such as excess and inadequate rainfall, reducing the probability of severe crop loss from weather-related events and generating a large impact on agricultural outcomes in areas hit by those weather shocks. Third, our analysis suggests that farmers in disadvantaged groups substantially benefit from having access to a digital advisory service. These findings point to the importance of access to customized, real-time information that meets the heterogeneous and dynamic needs of smallholder farmers.

Keywords: Agriculture, digital extension service, heterogeneity

*International IRB approval (Study 2681) was obtained from Health Media Lab. Authors can be contacted at Harigaya (tharigaya@precisiondev.org) and Zhu (jzhu@precisiondev.org). The authors would like to thank Caitlin McKee for helpful comments. Anjaney Singh, Sannihit, Deepak Punia, and Alex Ramirez provided outstanding research support. Usual disclaimers apply.

1 Introduction

Over two billion farmers and their family members work on small farms globally, the majority of whom live in poverty. Climate change, soil erosion, water scarcity, and increasing land constraints present new challenges to smallholder agriculture. Agricultural productivity is sensitive to these changing environments and local conditions. Yet, the vast majority of smallholder farmers have historically had little to no high-quality agricultural advice.

With advances in communication technologies and the rapid spread of mobile phones, digital technologies have transformed the delivery of agricultural information and services in low- & middle-income countries (LMICs). The use of mobile phones allows more customized information to reach a large number of farmers at the right time. Many LMIC governments now direct significant resources to incorporate digital technologies in extension services to improve their reach and effectiveness.

Existing evidence suggests that mobile phone-based agricultural information services can influence farmer behaviors (Cole and Fernando 2021; Fabregas et al. 2025) and improve agricultural outcomes (Arouna et al. 2021; Casaburi et al. 2019; Subramanian 2021). However, previous research offers limited insights on how the use of these services and their impact may vary across farmer characteristics. The key advantage of digital agricultural extension is its ability to deliver customized information at scale, serving diverse farmer needs at a low marginal cost. A better understanding of how well existing services cater to different farmer groups — in particular, disadvantaged groups, including women, low-literacy, poorer, and less connected farmers — could offer policy and design insights, helping to increase the returns on future investments in digital agriculture.

This report investigates these questions using the data from digital agricultural advisory services implemented by Precision Development (PxD) in India. PxD works with governments and other partners to design and scale mobile phone-based information services to millions of farmers across South Asia and Sub-Saharan Africa. In India, PxD and its partners have reached approximately 16.5 million farmers across nine states with customized digital agricultural advisory services. These services often include comprehensive advice on specific crop and livestock value chains and other relevant information, such as government subsidy schemes or weather information, throughout the agricultural season. The service operation is designed to be feasible and sustainable for low-resource partners.

Our analysis sheds light on the following two questions:

1. What are the characteristics of farmers who use mobile phone-based information ser-

vices? In particular, are poorer farmers, those with smaller farms, farmers that have fewer information sources, less educated farmers, or female farmers more or less likely to use these services?

2. How does the impact of a digital agricultural advisory service vary by farmer characteristics and real-time weather conditions?

We consider two types of usage constraints. First, smallholder farmers may face physical constraints in using mobile phone advisory services, for instance, because of unreliable access to mobile phones and network connectivity. Second, disadvantaged farmer groups face social and behavioral constraints, such as mobile literacy, lack of decision-making power, and limited ability to act on the advice. These two types of constraints are likely correlated but may have distinct implications for the usage and impact of digital advisory services.

Our analysis suggests that the majority of farmers who gain access to a digital agricultural advisory service successfully use the service. On average, well above half of the farmers registered for the service engage with the service in any given year across two services that have been operating for two to six years. Usage patterns across time of the day and advisory topics are context specific and also vary substantially within each service. In a randomized evaluation among rice farmers in Odisha, we find that the level of service engagement and the impact of the service are largest in areas hit by certain types of weather shocks, and that farmers with low socioeconomic characteristics benefit more from the digital service. Lastly, the level of engagement does not necessarily indicate the magnitude of service impacts. Farmers with lower engagement could still experience larger improvements on practices and gains on agricultural outcomes.

2 Service description, data and key variables

We use data from PxD's two digital advisory services: Ama Krushi (AK), co-designed with the Department of Agriculture and Farmers' Empowerment in Odisha, and Coffee Krishi Taranga (CKT), co-designed with the Coffee Board of India (CBI) and serving farmers in Andhra Pradesh, Karnakata, Kerala, and Tamil Nadu. Both services use a voice-based platform and deliver information to users' mobile phones. Farmers receive weekly audio messages with timely and locally relevant agricultural advice on their mobile phones. We refer to these pre-recorded messages as "outbound" calls. Farmers can also call into a free hotline to record agricultural questions that are then answered by local agronomists within 48 hours; they can listen to past outbound advisory messages and access their own inbox containing their history of questions and answers. We refer to these calls which farmers initiate as “inbound” calls. Farmers are registered for the service through a profiling call, where they answer approximately 10 questions about their demographic characteristics (e.g., gender, age, and education level) and crop and land characteristics (e.g., crop type, cultivation area, and irrigation choice).[1]

2.1 Ama Krushi

Ama Krushi is a a digital service co-designed by PxD and the Department of Agriculture and Farmers' Empowerment in Odisha in 2018.[2] It provides agricultural advice on 21 crops, livestock and fisheries to millions of farmers in Odisha, India. Odisha is one of the poorest states in India, with the majority of rural households engaging in rice farming. The advice is customized by farmer's preferred language, crop profile, location, land type, sowing method, and irrigation type reported in the profiling survey. The key agricultural topics include land preparation, seed varietal selection, sowing, nutrient management, pest and disease management, harvest and post-harvest management, and market price information. Those advisory messages are delivered according to the crop calendar and have minimal repetitions within one season. In addition, the service uses available real-time information on weather events and pest outbreaks to send relevant prevention and mitigation advice. Specifically, three types of weather-related advisory messages are provided: (i) advice on precautionary practices that could improve plant resilience to weather shocks, (ii) advice on real-time preventative practices that could mitigate potential damages of weather shocks, and (iii) advice on reactive management practices that could minimize the damage of weather shocks. Table 1 presents some topic examples of each type of advisory message.

Ama Krushi was fully transitioned to the government in 2022. Since then, the Government has continued to scale the service, reaching over 6.8 million farmers in the state as of 2024. Before the transition, a rigorous impact evaluation was initiated with 13,675 rice farmers from 2021 to 2023 to measure the impact of Ama Krushi on farmers' agricultural outcomes. The details of the service and the randomized evaluation are described in Cole et al. (2024) and available on PxD's website. It is worth noting that before Ama Krushi was launched, the state government largely relied on the network of public extension agents to disseminate information to farmers, but the majority of farmers had no interaction with

1. In some services, a small proportion of farmers are registered for the service without a profiling call. Our analysis focuses on profiled farmers, since the level of customization is limited for unprofiled farmers.

2. The program was co-funded by the Government of Odisha (GoO) and the Bill and Melinda Gates Foundation.

these agents because of the low agent-to-farmer ratio with roughly 4,900 agents serving nearly eight million farmers in the state.

2.2 Coffee Krishi Taranga

Coffee Krishi Taranga service is a digital service launched in 2019 in collaboration with the Coffee Board of India (CBI). This service provides advisories on coffee and spice cultivation across four states. The advice is customized by farmer's preferred language. The advisory topics include soil preparation, planting techniques, nutrient management, pest and disease control, harvest methods, and post-harvest management. Additionally, some advisory messages target farmers cultivating specific coffee varieties. Coffee Krishi Taranga also provides information on local and international coffee market prices in real time. The service was initially launched and scaled across Karnataka, Kerela, and Tamil Nadu and has now expanded to Andhra Pradesh. Coffee farmers, on average, cultivate larger land and earn more compared to rice farmers in Odisha, with the exception of Andhra Pradesh. Andhra Pradesh is characterized by low rainfall and indigenous farmer populations cultivating coffee with low levels of input use and market access. The service has reached 133,000 farmers across the four states since its inception, and it is used by approximately 113,000 coffee growers in 2024. A more detailed overview of Coffee Krishi Taranga can be found on PxD's website.

2.3 Data

2.3.1 Administrative service usage data

PxD's service platform records all interactions with its users. The farmer database contains the information collected during the profiling survey. Each outbound call record includes the message design information (e.g., advisory message ID, length of the message, and language) and farmer interaction (e.g., time of the call, whether it was picked up, how long a farmer stayed on the line). Using these data, we first construct three outcomes at the unique advisory message level[3]: 1) a pick-up dummy indicating whether the farmer picked up a specific call, 2) a listening rate indicating the share of the advisory call heard by the farmer, conditional on picking up the call[4], and 3) a dummy indicating whether a farmer listened to at least 80% of the advisory call as a proxy for receiving the key pieces of information

3. An advisory call is automatically rescheduled up to twice with a few-hour gap between each call if a farmer does not pick up the previously attempted call.

4. This measure is capped at value 1.

from the call. We consider this third variable as our key engagement outcome, representing a measure of the overall volume of agricultural content received by a farmer.[5]

We then aggregate these unique advisory message-level outcomes to construct farmer and farmer-season (or farmer-year) level outcomes. For example, we calculate whether a farmer ever listened to an advisory call, and also whether a farmer listened to at least one advisory call in a given season/year. Farmers in Odisha cultivate twice a year, and thus, we largely use farmer-season outcomes, whereas outcomes for coffee farmers are aggregated at the year level because coffee is cultivated throughout the year.

To examine the usage of PxD's digital advisory services, we use the engagement data from 6,837 Ama Krushi users who were part of the randomized evaluation between 2021 and 2023 and from 81,699 Coffee Krishi Taranga users between 2018 and 2023 that are all registered users who responded to a profiling call. We focus our analysis of Ama Krushi on the evaluation sample because of the availability of detailed demographic information and agricultural outcomes. We also note that the analysis reported here is limited to farmers' engagement patterns in the outbound service (automated push call service) due to low usage of the inbound (or hotline) service.[6]

2.3.2 Survey data from a randomized evaluation of Ama Krushi

To examine the differential impact of digital advisory by farmer characteristics, we use three rounds of survey data collected from the sample of 5,204 farmers in the aforementioned randomized evaluation. The survey data provide information on agricultural practices, i.e., self-reported adoption of key inputs and practices, and agricultural outcomes, including rice yield (kg/ha), rice harvest (ha), and whether a farmer experienced rice crop loss.[7] Additionally, the survey data offer detailed information on farmer's demographic and socioeconomic characteristics, including the gender of the registered user, education levels, incomes, house materials, and cultivation areas, as well as village characteristics on infrastructure and available services. The details of the evaluation design and data are summarized in Cole et al. (2024).

For the analysis of this evaluation sample, we also extract daily rainfall data at the block level from the state weather monitoring portal and government reports on damages in rice

5. The advisory call length typically varies from 60 to 90 seconds. In the last 15 seconds, the call typically reminds the farmer about the hotline service and reads out the hotline number.

6. Less than 5% and 4% registered farmers have successfully used the inbound service in the Ama Krushi service and Coffee Krushi Taranga service, respectively.

7. The measurement of crop loss is only available for the second year.

cultivation from extreme weather events.[8] Using those two public data sources, we identified four major weather events that affected rice cultivation in parts of study area and years — excess rainfall and cyclone in Kharif 2021, and river floods and scarce rainfall in Kharif 2022.[9] We are interested in examining how farmers' engagement patterns vary across rainfall situations and weather shocks.

2.3.3 Measurement of phone access and farmer's socioeconomic characteristics

Throughout this report, we consider six sets of socioeconomic characteristics: (1) mobile phone access, (2) gender of the registered user or women's engagement in agricultural decision-making[10], (3) education levels, (4) income amounts and assets, (5) land holdings, and (6) local infrastructure and service access. We define these characteristics as follows.

1. **Mobile phone access**: For the Ama Krushi sample, we use baseline data on whether a farmer shared the primary phone with other household members as a dummy indicator of mobile phone access.

2. **Women's engagement in agricultural decision-making**: We use the gender of the registered user across the two services. However, qualitative data from Odisha suggests that women in the household, even when the registered user is male, access information through the service. We thus also consider the measure of joint agricultural decision-making reported in the baseline survey for the Ama Krushi sample.

3. **Education level**: For the Ama Krsuhi sample, we create an index using available measures of years of education and literacy of the registered user. Specifically, we use information on whether a farmer can write, can read, completed any formal schooling, completed the 5th grade, completed the 8th grade, and completed the 10th grade. For the Coffee Krishi Taranga sample, we use a categorical variable to indicate the education level. It takes the value of 1 for not completing any formal schooling, 2

8. The daily rainfall data are extracted from the government's weather monitoring portal and government's reports on damage on rice cultivation from climate events are extracted from Special Relief Commissioner.

9. We define excess rainfall as receiving more than 250 mm rainfall over two days in the period of August 16 to October 15 in 2021, a cyclone as receiving more than 50 mm rainfall over two days in the period of December 4 to December 10 in 2021, and scarce rainfall as receiving less than 450 mm rainfall over the period of August 16 to October 15 in 2022. We define river flooding using the government's incidence report.

10. Unfortunately, women farmers represent a small proportion in our study sample (15%), with significant baseline imbalance in key outcomes, including agricultural yield and harvest, between the treatment and control groups (Appendix Table A5). Therefore, we consider an alternative measure of women's engagement in agricultural decision-making.

for completing some primary education, 3 for completing some secondary education (grades 6-10), 4 for completing higher secondary education (grades 11-12), and 5 for completing college and above.

4. **Wealth index**: For the Ama Krushi sample, we create an index across household income from the previous year, whether a farmer's house is constructed entirely with solid materials, and whether it is constructed partially with solid materials. We do not have any wealth measure for the Coffee Krishi Taranga sample.

5. **Size of cultivation area**: We construct a relative measure of the size of the cultivation area within each service and geography using the data from the baseline survey (Ama Krushi) or the profiling survey (Coffee Krishi Taranga).

6. **Infrastructure and service access**: For the Ama Krushi sample, we identify less-connected villages by creating a village-level index of paved roads and the presence of a post office, a bank, a computer center, a health clinic, and a secondary school, collected during the baseline survey for the randomized evaluation. We do not have any infrastructure measures for the Coffee Krishi Taranga sample.

The indicator variables for low levels of education, wealth, and land holdings are created by identifying farmers who have below-median index value within each panchayat for the Ama Krushi sample and within each state for the Coffee Krishi Taranga sample; the indicator variable for low levels of infrastructure and service access is created by identifying villages that have below-median index values within a panchayat.[11]

We additionally control several other socioeconomic characteristics of farmers — age, use of fertilizer, access to irrigation, and whether the primary phone is a feature phone — in the analysis, but they are not the focus of the heterogeneity examination. The analysis excludes up to 2.5% of farmers in the study sample for whom we do not have the relevant baseline data for the Ama Krushi sample and 9.1% of farmers for whom we do not have the profiling data for the Coffee Krishi Taranga sample.

3 Who use mobile phone-based advisory services?

In this section, we present descriptive analyses of PxD's administrative data to investigate the patterns in service usage. We start by presenting the summary statistics of farmer characteristics and the engagement statistics of the two services by geography. We then discuss

11. A panchayat is an administrative unit that is above the village unit.

the results of the regression analyses which explore correlations between farmer characteristics and service usage. Finally, we take a granular look at usage patterns, breaking down the data by two message design features — call timing and message content topic — to examine whether usage patterns vary by farmer group. We also examine whether and how usage patterns change by weather conditions. One important caveat is that these design features were not randomly assigned across farmers or advisory messages in either of the services. Advisory calls are typically scheduled for all farmers at once on a particular day or days of the week, and allocated to different time slots if there is no sufficient phone line capacity to send them out at once.

3.1 Summary statistics of farmer characteristics and service engagement

Table 2 presents the summary statistics of farmer profiles by service and geography. Each service has about 15% female users. On average, farmers have 2.4 acres of cultivation land in Odisha (Panel A), 2 acres in Andhra Pradesh (Panel B), and 7.5 acres in the other three coffee states (Panel C). The majority of farmers use a feature phone as their primary phone. In both services, most farmers rely on rainfall: less than half of farmers across geographies have access to functioning irrigation. Farmer characteristics reflect the substantially different coffee farming contexts between Andhra Pradesh and the other three states — Karnataka, Kerala, and Tamil Nadu. On average, farmers in Andhra Pradesh have lower levels of education and use fewer inputs, including irrigation and fertilizer, compared to those in the other three states.

Table 3 presents an overview of the engagement statistics by service and geography.[12] Overall, we observe sustained engagement with the advisory service. On average, farmers listen to 23-29% of advisory calls across three services with varying years of operation, between two and six years. While the proportion of advisory calls farmers pick up varies from 46-60% across these services, the listening rate once the call is picked up is remarkably consistent at around 60%. At the farmer-level, the likelihood of engagement is substantially lower in Andhra Pradesh, with less than 70% of farmers ever listening to the advice, compared to other geographies where approximately 90% of farmers used the service at least once.

The service usage data also suggests that the call retry design could help mitigate unreliable cellphone network to some extent. Recall that the calls are automatically rescheduled up to twice if a farmer does not pick them up. For the first call attempt (not shown), 30%

12. As discussed earlier, an advisory call is automatically rescheduled up to twice with a few-hour gap between each call attempt if a farmer does not pick up the previously attempted call. We use data on the final attempted calls of each advisory message for this analysis.

of advisory messages are picked up in Andhra Pradesh, compared to 58% in the other coffee states. After three attempts, the pick up rate increases by 16 percentage points in Andhra Pradesh (an increase of 53% from 30 to 46%), whereas it only increases by 2 percentage points (an increase of 3.5%) in the other coffee states.

We next illustrate the temporal changes in service usage in Figures 1 and 2. Overall engagement remains consistent over the first two years in Odisha and Andhra Pradesh, whereas the average usage level has decreased in the other three coffee states. However, no prominent pattern in engagement gaps between existing and new users emerges in these figures, suggesting that engagement does not linearly decline with a longer tenure with the service.[13]

3.2 Correlation between farmer characteristics and service engagement

To understand who are more likely to use the service successfully, we explore the determinants of active service usage using association analysis between farmer characteristics and the share of advisory messages with at least 80% content listened to, as a measure of the intensity of service usage. Results for Ama Krushi and Coffee Krushi Taranga are reported in Table 4 for Ama Krushi and Table 5 for Coffee Krushi Taranga, respectively.[14] We highlight four patterns observed in these analyses.

First, usage patterns by farmer characteristics are highly context-specific. For instance, low levels of education are consistently and strongly correlated with low intensity of engagement for Ama Krushi and Coffee Krishi Taranga in Andhra Pradesh, whereas they are strongly correlated with *high* intensity of engagement for Coffee Krishi Taranga in the other three states. Similarly, female farmers are less likely to engage in the service in coffee states, whereas this correlation is not prominent in Odisha. Second, a physical constraint in mobile phone access is persistently correlated with low intensity of engagement: in Odisha, farmers sharing the primary phone with other household members listen to 20% fewer calls. Third, correlations between farmer characteristics and the intensity of engagement remain largely persistent over time, spanning four agricultural seasons for Ama Krushi and four years for Coffee Krishi Taranga. This pattern is especially evident for invariable or hard-to-change characteristics, such as education levels, female farmers, and small landholdings.

13. Once a farmer is registered for the service, few farmers ($< 1\%$) opt out of the service. Higher engagement among existing users across some years, thus, is not driven by opt-out users.

14. We also present the same set of correlation analyses using *any* service usage in Appendix Table A1 and A2. Results on the correlations with the extensive margin of service usage closely follow the patterns as observed in the correlations with the intensive margin.

One of the key features of Ama Krushi was the real-time advice to help farmers navigate adverse weather events. We explore if exposure to adverse weather shocks in the previous season — defined by any incidence of excess or inadequate rainfall during the growing season — affects engagement in this service. As shown in Table 4, while farmers who experienced weather shocks in the previous season are more likely to engage in the service in the first year, this pattern does not sustain in the second year. Farmers face numerous micro-climate shocks throughout agricultural seasons. A granular analysis tracking usage within a season, instead of across seasons, might be more appropriate to assess the influence of those local climate shocks on the propensity to use the service. We will discuss this investigation in the next subsection 3.3.

3.3 Variation of engagement with service designs and weather realizations

Turning to granular variations in how farmers engage with customized advisory services, we start with variations in two design aspects. First, we consider the call timing (hours of the day and day of the week). The timing of advisory calls may interact with both physical and social constraints farmers face in using mobile phones and listening to advisory calls. For instance, farmers sharing a phone with family members may not have mobile phone access to receive advisory calls during certain times of the day or days of the week; or farmers engaging in casual agricultural labor may have less flexibility to pick up advisory calls during agricultural work on the field. Second, we examine engagement variation by advisory topic. We expect the demand for advice would vary across different agricultural topics. One key question is whether differential engagement by farmer characteristics also varies across agricultural topics, for instance, because of differential demand.

We first map engagement levels in the first attempted calls of each advisory message by hours of the day and days of the week. Figures 3 and 4 track the average share of the calls of which farmers listened to at least 80% of the content for Ama Krushi and Coffee Krishi Taranga, respectively.[15] Overall, we see a significant variation in the share of calls listened to across time windows throughout the day and the week. In the worst time slots, less than 5% of the calls are listened to, whereas this share increases to more than 20% in Ama Krushi and up to 60% in Coffee Krishi Taranga in the best time slots. It is worth noting that engagement levels are consistently lower in Andhra Pradesh, where mobile connectivity is unreliable, compared to that in the other coffee states.

15. We limit this analysis to the first attempted call for each advisory message, because the timing of additional attempted calls are endogenous to whether farmers pick up the previous calls or not.

We further break down this analysis by farmer characteristics to assess how engagement gaps between farmer groups vary by the time of the day or the day of the week. Results are reported in Appendix Figure A1-A4.[16] Overall, engagement gaps by farmer characteristics follow similar trends over the course of the day and fluctuate substantially. In a few selected cases, however, figures point to time windows where the gaps appear to reduce. For instance, the engagement gaps between female and male farmers are apparent only during mornings among Coffee Krishi Taranga users in Andhra Pradesh; the gender gap in engagement also looks more muted during evenings among Coffee Krishi Taranga users in other states. These granular patterns are difficult to discern through simple visualization and may warrant the use of machine learning and other more advanced techniques. For instance, Athey et al. (2024) use machine learning to show that data-driven customization on optimal call delivery time could potentially increase engagement of vulnerable populations, highlighting the value of data-driven customization.

Looking at the engagement levels across message topics, the average share of calls of which farmers listened to at least 80% of content is relatively consistent across agronomic topics, between 22-30% for Ama Krushi, with the exception of messages on market prices (Figure 5), and 24-32% for Coffee Krishi Taranga (Figure 6). The "welcome" message when a farmer is first registered for the service has the highest listening rate across geographies. The relatively constant listening rates across topics sent across the season also suggest that farmers' engagement does not diminish within the season. When the analysis is broken down by farmer characteristics, we largely observe the same patterns in engagement gaps across advisory message topics (Figure 5 and 7). Our data come from geographies where the majority of farmers cultivate one predominant crop (coffee or rice). Engagement gaps by farmer characteristics may vary more across value chains than across topics within a value chain.

Finally, we investigate if adverse weather shocks lead to immediate and substantial changes in service engagement. To assess this, we aggregate rainfall and engagement levels at the weekly level and plot how engagement metrics track the volume of rainfall. We use the share of advisory messages with at least 80% content listened to (Figure 8) and the share of advisory messages picked up (Figure 9) for this analysis. In particular, we are interested in weeks with "too much" or "too little" rainfall. In general, farmers in areas hit by weather shocks show higher engagement with the service, compared to farmers in areas without

16. We only show the analysis by gender for the Coffee Krishi Taranga service, as analyses by other farmer characteristics show similar patterns. Other results are available upon request.

weather shocks. While engagement levels in areas hit by excess rainfall spiked immediately following weather events in 2021, the graphs do not allow us to determine whether the observed spikes are caused by the adverse weather events, or simply reflect baseline differences in engagement levels.[17]

4 How does the impact of a mobile phone-based advisory service vary by farmer characteristics?

Our second objective is to examine how the impact of PxD's digital advisory service varies by farmer characteristics. We first summarize the key results from the randomized evaluation of Ama Krushi among rice farmers in Odisha, reported in Cole et al. (2024); we then present findings from additional analyses investigating heterogeneous treatment impacts by disadvantaged farmer groups.

4.1 Methodology

To estimate the heterogeneous impact of Ama Krushi by farmer characteristics, we use the following specifications:

$$Y_{it} = \alpha + \beta_1 T_i + \beta_2 T_i Z_i + \beta_3 Z_i + \psi Y_{i0} + X'_{i0}\delta + S'_{i0}\eta + \gamma_s + \epsilon_{it}, \tag{1}$$

where Y_{it} stands for outcomes of interest of farmer i in year $t \in (1, 2)$, with $t = 1$ and 2 indicating the Year 1 (Kharif 2021) season and the Year 2 (Kharif 2022) season, respectively, T_i is the treatment dummy indicating been offered access to Ama Krushi, Z_i is the farmer characteristic of interest, $T_i Z_i$ represents the interaction between the treatment indicator and the farmer characteristic of interest, Y_{i0} is the pre-intervention value of the outcome measured at baseline, X_{i0} is a vector of exogenous control variables, S_{i0} is a vector of survey design variations including indicators for the survey modality, whether the final survey modality is switched from the initial assignment, and the timing of follow-up data collection, and γ_s represents the panchayat-year fixed effects. We use Huber-White robust standard errors in analyses that examine heterogeneity by farmer characteristics, and cluster standard errors at the village level in analyses that examine heterogeneity by village characteristics.

17. The differences in pick-up rates between excess rainfall area and no excess rainfall area were highest in the excess rainfall shock week (6.7 percentage points) and the cyclone shock week (7.5 percentage points).

4.2 Key findings of the Ama Krushi impact evaluation

We highlight three sets of findings from the evaluation of Ama Krushi in Cole et al. (2024). First, a high proportion of farmers registered for and engaged with the service over the two years during the evaluation. Among 2,602 farmers who were offered access to Ama Krushi and surveyed, 94% in the first year and 84% in the second year accessed the service; 88% in the first year and 77% in the second year listened to at least one agricultural advisory message during the Kharif season. An average farmer with access to Ama Krushi listened to approximately 25% of advisory calls, or 9-10 advisory messages, over the six-month season.

Second, access to Ama Krushi leads to improvements in agricultural knowledge, practices, and production outcomes on average. The treatment increases the summary index of self-reported adoption behavior across 13-14 practices by approximately 0.05-0.1 standard deviations in each year. Cole et al. (2024) also observe average per-season increases in rice yield (harvest per unit of land) by 1.74% and harvest by 4.12% over the control means during the evaluation years. These estimates are at par with existing impact evidence from prior studies of digital agricultural information services. For instance, a meta-analysis across seven digital agriculture programs in Asia and Africa shows a 4% increase in yield on average (Fabregas, Kremer, and Schilbach 2019).

Third, Ama Krushi appears to have the largest impact in areas hit by some (but not all) weather shocks. Treated farmers, on average, report lower likelihoods of crop losses — including a 10% reduction in the likelihood of losing more than half of their crops (severe crop loss) — in the second year in which we collected data on crop losses. This effect is driven primarily by a 25% reduction in severe crop loss due to pests and diseases, and weather events other than floods. Further investigation suggests that the impact of Ama Krushi is concentrated in areas hit by excess rainfall that caused submergence in 40% of the study blocks in the first year and in areas that received inadequate rainfall in the second year. Point estimates indicate a 6.8% higher yield and a 9% higher total rice production by treated farmers than control farmers in areas affected by excess rainfall in the first year, and a 21% reduction in the likelihood of severe crop loss among treated farmers compared to control farmers in areas hit by inadequate rainfall in the second year. One important note is that the service does not help farmers cope with *every* shock. For instance, the treatment impact in areas hit by sudden river flooding in the early growing season of the second year is close to zero across all agricultural outcomes.

4.3 Impact by baseline productivity

In this evaluation, the experiment randomization was stratified by panchayat of residency (administrative unit with a collection of 6-7 villages on average) and self-reported productivity at baseline. Its pre-analysis plan (PAP) specified the heterogeneous treatment impact analysis by baseline yield. Cole et al. (2024) show that Ama Krushi significantly increased total production among farmers who had low yield at baseline partially by encouraging them to cultivate larger land areas in both years. Point estimates on the adoption index nearly double from the first to the second year for this farmer group, suggesting a sustained impact on farming practices, whereas the large impact on the adoption index in the first year among high-yield farmers attenuates in the second year.

4.4 Impact for low socioeconomic groups

In this section, we explore the program impact by additional indicators that reflect farmer's socioeconomic characteristics. Specifically, we consider education levels, wealth levels, size of cultivation area, infrastructure and service access, and women's engagement in agriculture (see Section 2.3.3 for definitions). We note that the analysis we present here is exploratory in nature. We did not stratify the random assignment of digital agricultural advisory by the socioeconomic characteristics we examine; neither did we pre-specify these additional analyses on heterogeneous treatment impact in the PAP.

Appendix Table A3 shows that key outcome variables are well-balanced between the experimental groups by the first four characteristics: the interaction term between the treatment indicator and each farmer characteristic is generally small and insignificant. Not surprisingly, baseline characteristics are correlated with agricultural outcomes. Farmers with low education and wealth indices are significantly less likely to adopt recommended practices and produce at lower levels at baseline. Farmers with small cultivation areas are also less likely to adopt recommended practices. Their large positive correlation with yield and large negative correlation with harvest are likely mechanical since the total cultivation area is highly correlated with the total rice cultivation area. In contrast, a low infrastructure index — farmers residing in villages with limited infrastructure and services — is not correlated with low levels of adoption or agricultural outcomes, suggesting that individual farmer's human capital and economic characteristics are better predictors of farming practices and outcomes.

Our study has a small sample of women, and women in the treatment group have significantly better agricultural outcomes at baseline compared to women in the control group

(Appendix table A4 Panel A). We consider households that reported jointly making agricultural decisions with their spouse — roughly 50% of the sample — as an alternative measure of women's engagement in agricultural decision-making. However, treated farmers who make joint decisions with their spouses are also significantly more likely to adopt recommended agricultural practices compared to their counterparts in the control group (Appendix table A4 Panel B). While we report the heterogeneous treatment impact by gender in Appendix Tables A5 and A6 for transparency, the observed differences in the impact may be driven by baseline differences between the experimental groups.

In Tables 6-9, we report the treatment impact by farmer characteristics on four outcomes: the adoption index separately for the first and the second year, yield and harvest using pooled data between the two years, and the likelihood of severe crop loss in the second year.[18] First, consistent with the pattern in the baseline data, low education and low wealth indices are strongly correlated with poor agricultural outcomes in the absence of Ama Krushi: Less-educated and poorer farmers in the control group have lower productivity and total harvest and a higher likelihood of severe crop loss compared to more-educated and wealthier farmers in the control group.

Second, the results across the four characteristics illustrate that farmers with low socioeconomic characteristics benefited from the service, with the exception of farmers who have small cultivation land. Tables 6 and 7 show that Ama Krushi significantly improved agricultural practices among farmers with low education and low wealth indices in both years, leading to economically meaningful improvements in agricultural outcomes (yield in Column (3), harvest in Column (4), and severe crop loss in Column (5)), even though the point estimates for these farmers are not always larger than for farmers with high education and wealth indices. Similarly, Table 9 shows a positive treatment impact on the adoption index in both years, albeit modest and less robust, for farmers residing in villages with low infrastructure indices, leading to large improvements across all agricultural outcomes (Columns 3-5). In contrast, the treatment impact among farmers with small cultivation areas is limited as reported in Table 8. The impact on the adoption index becomes small and insignificant in the second year, and we do not observe significant average improvements in agricultural outcomes over the two years. An average farmer with a small cultivation area

18. Here, we use the "transplanting" summary index which includes practices that are relevant to the transplanting cultivation method. As reported in Cole et al. (2024), Ama Krushi provided a broader set of advice and generated a larger impact on farming practices for farmers who practiced transplanting than for those who practiced broadcasting. This analysis is limited to 83% of farmers in the study sample who reported practicing transplanting at baseline.

had 0.94 acres of paddy land at baseline, compared to 2.7 acres for an average farmer with a large cultivation area. Without economies of scale, costly practices that are profitable for an average farmer may not be profitable for very small land: even with modest improvements in agricultural productivity, a small cultivation area means limited aggregate benefits, unless they can expand their cultivation areas.

Third, the large, positive impact of Ama Krushi among farmers with low education index is particularly noteworthy given that these farmers engaged *less* with the service. They listened to 20% less agricultural content on average in both years, as shown earlier (Table 4). These results suggest that farmers with low levels of education and literacy engage less with the service on average, but the service may generate a larger impact for those who actively use it compared to more literate and educated farmers who tend to adopt more of the recommended practices at baseline.

5 Conclusion

This report summarizes the analysis of PxD's administrative data on the usage of two digital advisory services across five states in India and survey data from an impact evaluation of PxD's digital advisory service in one state. The following insights emerge from our analysis:

- The majority of farmers who are registered for a digital advisory service receive agricultural advice at least once. Across three services that have been operating for 2-5 years, the average proportion of farmers who engage in the service in a given year ranges from 64% to 90%.

- Both physical constraints, such as access to mobile phones and network connectivity, and farmer-level socioeconomic characteristics are highly correlated with the level of engagement. In geographies with low network connectivity, a smaller proportion of farmers successfully use the advisory service, but the intensity of usage among those who use the service is at par with users in better-connected geographies. Farmers with a primary phone shared with family members, female farmers, and farmers with low levels of education tend to have low engagement levels.

- These correlations are context-specific but persistent within a context over time. Farmer characteristics that are strongly correlated with high levels of engagement in the first year continue to be the strong predictors of engagement over the following 2-4 years.

- The level of engagement varies substantially across time of the day and message topics. However, descriptive analysis does not reveal differential patterns by selected socioeconomic characteristics we examine: engagement gaps by gender of the user, education levels, and use of shared phones are largely persistent across call time and message topics.

- The level of engagement also varies by weather realization. Farmers in areas that experienced weather shocks tend to engage with the service more.

- The impact of PxD's digital advisory among rice farmers in Odisha is largest in areas affected by certain weather shocks. Access to the service increases total production by nearly 10% in areas hit by excess rainfall in one year and reduces the likelihood of severe crop loss by 21% in areas affected by inadequate rainfall in another year.

- The exploratory analysis of heterogeneous treatment impact by farmer characteristics suggests that farmers with low socioeconomic characteristics, including farmers with low productivity, low education, and low wealth levels, as well as farmers in less-connected villages, substantially benefited from the service. However, the impact of the service on agricultural outcomes is somewhat muted for farmers with small cultivation areas, where economies of scale are difficult to achieve.

- Relative engagement levels do not predict relative magnitudes of impact. In our data from the digital advisory service among rice farmers in Odisha, those with low levels of education engage less in the service, but the impacts on adoption behavior and agricultural outcomes are as large as, or potentially larger than, the impacts for farmers with high levels of education. Similarly, farmers residing in less-connected villages use the service as much as farmers in better-serviced villages, but the impact of access to the service on agricultural outcomes is notably larger, suggesting that the marginal value of the digital advisory service may be higher for less-connected villages.

Overall, our analysis suggests that service usage patterns vary widely across contexts and farmer characteristics but that the benefits of customized digital advisory services do reach vulnerable smallholder farmer populations and help farmers cope with certain types of weather shocks. The variations in usage patterns and magnitudes of impact underscore the potential value of improved customization and targeting of advisory messages.

6 Tables and Figures

6.1 Tables

Table 1: Weather-related advisory messages (Ama Krushi)

Type of advisory messages	**Examples of specific advisory topics**
On precautionary practices	Stress-tolerant seed (i.e., flood-tolerant seed, drought-tolerant seed), sowing timing (for broadcasting, transplanting).
On real-time preventive practices	How to deal with scanty rainfall, crop protection prior to heavy rainfall.
On reactive management practices	Sowing paddy post flood, post flood pest management, post flood nutrient management.

Table 2: Summary statistics of farmer characteristics

Variable	Mean	SD	Median	N
Panel A: Ama Krushi Service				
Age	44.274	9.750	45	6,818
Female	0.147	0.354	NA	6,818
Joined decision making	0.489	0.500	NA	6,147
Years of education	6.070	4.296	7	6,762
Total cultivation size (acre)	2.415	1.683	2.0	6,798
Have access to irrigation	0.466	0.499	NA	6,818
Computer centers in the village	0.258	0.438	NA	2,594
Primary phone: shared regularly	0.598	0.490	NA	6,786
Primary phone: feature phone	0.619	0.486	NA	6,818
Panel B: Coffee Krishi Taranga Service: Andhra Pradesh				
Age	40.035	10.609	39	5,423
Female	0.131	0.337	NA	5,423
Education level	2.480	1.402	2	5,419
Coffee plantation size (acre)	1.990	6.673	1.0	5,423
Has functioning irrigation	0.0116	0.107	NA	5,420
Uses any fertilizer	0.143	0.350	NA	3,868
Intercropping	0.730	0.444	NA	5,422
Primary phone: feature phone	NA	NA	NA	0
Panel C: Coffee Krishi Taranga Service: Karnataka & Kerala & Tamil Nadu				
Age	52.053	12.359	52	75,981
Female	0.148	0.355	NA	76,247
Education level	3.534	1.072	3	73,166
Coffee plantation size (acre)	7.512	117.404	2.8	76,232
Has functioning irrigation	0.493	0.500	NA	70,262
Uses any fertilizer	0.961	0.194	NA	741
Intercropping	0.883	0.322	NA	76,247
Primary phone: feature phone	0.520	0.500	NA	73,981

Notes: These statistics are generated using survey data from a randomized evaluation of Ama Krushi and profiling data for Coffee Krishi Taranga. In the Coffee Krishi Taranga data, the values of "education level" variable refer to 1 - no schooling, 2 - primary education, 3 - secondary education (grade 6-10), 4 - higher secondary education (grade 11-12), and 5 - college and above.

Table 3: Summary statistics of service engagement

Variable	Mean	SD	Median	N
Panel A: Ama Krushi Service				
Advisory message level				
Pick up rate	0.479	0.500	0.000	582,618
Listened to $\geq$ 80% content	0.242	0.429	0.000	582,618
Listening rate	0.597	0.425	0.843	279,107
Farmer level				
Any engagement (listened to at least one message)	0.925	0.264	1.000	6,818
Proportion of years with any engagement	0.897	0.280	1.000	6,818
Panel B: Coffee Krishi Taranga Service - Andhra Pradesh				
Advisory message level				
Pick up rate	0.463	0.499	0.000	137,103
Listened to $\geq$ 80% content	0.230	0.421	0.000	137,083
Listening rate	0.604	0.413	0.788	63,421
Farmer level				
Any engagement (listened to at least one message)	0.697	0.460	1.000	5,423
Proportion of years with any engagement	0.635	0.448	1.000	5,423
Panel C: Coffee Krishi Taranga Service - Karnataka & Kerala & Tamil Nadu				
Advisory message level				
Pick up rate	0.604	0.489	1.000	4,184,104
Listened to $\geq$ 80% content	0.292	0.455	0.000	4,183,513
Listening rate	0.602	0.404	0.722	2,528,663
Farmer level				
Any engagement (listened to at least one message)	0.925	0.264	1.000	76,276
Proportion of years with any engagement	0.665	0.293	0.667	76,276

Notes: These statistics are generated using PxD's administrative service data. For Ama Krushi, the data cover the period from Kharif 2021 to Rabi 2023. For Coffee Krishi Taranga, the data cover the period from 2018 (the inception of the service) to December 31, 2023, but exclude 31% of advisory calls with missing information on the call length. The sample for Coffee Krishi Taranga is restricted to farmers who have been profiled. "Pick up rate" is a dummy indicating whether a farmer picks up the advisory call. "Listened to $\geq$ 80% content" is a dummy indicating whether a farmer listened to at least 80% of the advisory call. "Listening rate" is calculated as the time that a farmer stayed on the line, divided by the total call length. This variable is capped at value 1 and missing for those who do not pick up the call. "Any engagement (listened to at least one message)" refers to farmers who listened to at least one advisory message sufficiently (i.e., more than 80% of the content) over the tenure of membership. "Proportion of years with any engagement" refers to the proportion of service years in which a farmer listened to at least one advisory message sufficiently. A service year is defined as June - May (Kharif and Rabi) for Ama Krushi; and a year count from individual farmer's profiling date for Coffee Krishi Taranga.

Table 4: Correlation between farmers characteristics and the intensity of service usage
[Outcome: The share of advisory calls that farmers listened to at least 80% of the content in a given season]
(Ama Krushi)

	1st year of enrollment		2nd year of enrollment	
	(1) in Kharif	(2) in Rabi	(3) in Kharif	(4) in Rabi
Age	0.001***	0.002***	0.003***	0.003***
	(0.000)	(0.000)	(0.001)	(0.001)
Female	0.006	-0.000	0.000	0.022
	(0.009)	(0.013)	(0.015)	(0.018)
Joined decision making	-0.013*	-0.014*	-0.022*	-0.026*
	(0.006)	(0.008)	(0.011)	(0.013)
Low edudcaion index	-0.058***	-0.060***	-0.051***	-0.052***
	(0.006)	(0.008)	(0.011)	(0.013)
Low wealth index	-0.008	-0.005	-0.011	-0.024**
	(0.006)	(0.008)	(0.010)	(0.012)
Small cultivation area	-0.007	0.001	-0.004	-0.009
	(0.006)	(0.008)	(0.010)	(0.012)
Low infrastructure index	-0.003	-0.014	-0.010	-0.010
	(0.010)	(0.014)	(0.010)	(0.012)
Primary phone: shared regularly	-0.056***	-0.058***	-0.050***	-0.061***
	(0.007)	(0.009)	(0.011)	(0.013)
Primary phone: feature phone	0.074***	0.079***	0.075***	0.076***
	(0.006)	(0.008)	(0.010)	(0.012)
Have access to irrigation	0.015**	0.023***	0.011	0.010
	(0.006)	(0.008)	(0.011)	(0.013)
Adverse rainfall shock in the pervious year	0.016**	0.015	-0.014	-0.001
	(0.007)	(0.009)	(0.014)	(0.016)
N	5758	5727	2086	2098
R^2	0.081	0.054	0.063	0.059
Average	0.274	0.260	0.214	0.224

Notes: The analysis reported in this table uses PxD's administrative data from Ama Krushi. The dependent variables are the shares of advisory calls of which farmers listened to at least 80% of the content in the 1st, 2nd, 3rd, and 4th agricultural seasons since registered for the service. All regressions control for the cohort dummy and district dummies. Robust standard errors are reported in parenthesis: * p<0.10, ** p<0.05, *** p<0.01.

Table 5: Correlation between farmers characteristics and the intensity of service usage

[Outcome: The share of advisory calls that farmers listened to at least 80% of the content in a given year]

(Coffee Krishi Taranga)

	Andhra Pradesh		Karnataka & Kerala & Tamil Nadu			
	(1)	(2)	(3)	(4)	(5)	(6)
	1st year	2nd year	1st year	2nd year	3rd year	4th year
Age	0.000	0.001***	0.003***	0.003***	0.003***	0.002***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.040***	-0.076***	-0.035***	-0.039***	-0.040***	-0.024***
	(0.010)	(0.016)	(0.002)	(0.002)	(0.004)	(0.008)
Low education	-0.030***	-0.037***	0.018***	0.018***	0.022***	0.021***
	(0.008)	(0.013)	(0.002)	(0.002)	(0.003)	(0.006)
Small coffee land	0.007	0.002	-0.008***	-0.011***	-0.013***	-0.007
	(0.007)	(0.011)	(0.002)	(0.002)	(0.003)	(0.005)
Has functioning irrigation	0.030	0.019	0.001	-0.005**	-0.002	-0.014**
	(0.027)	(0.040)	(0.002)	(0.002)	(0.003)	(0.006)
Uses any fertilizer	(0.027)	(0.040)	-0.051	-0.019	-0.016	0.139***
	(0.012)	(0.017)	(0.051)	(0.057)	(0.072)	(0.053)
Intercropping	0.010	0.052***	0.022***	0.007	0.012**	0.006
	(0.007)	(0.012)	(0.004)	(0.004)	(0.006)	(0.012)
Feature phone			0.017***	0.013***	0.004	0.004
			(0.002)	(0.002)	(0.003)	(0.005)
Num. Observations	5419	2526	73049	64455	35947	10467
Mean of Outcome	0.221	0.246	0.311	0.242	0.235	0.195

Notes: The analysis reported in this table use PxD's administrative data from Coffee Krishi Taranga. The sample is restricted to farmers who have been profiled and excludes advisory calls with missing information on call length. The dependent variables are the shares of advisory calls of which farmers listened to at least 80% of the content in the 1st, 2nd, 3rd, and 4th year since registered for the service. All regressions control for missing dummies for each covariate that indicate missing values are imputed with the median value within the state. District-level fixed effects are included. Robust standard errors are reported in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Heterogeneous treatment impact by education level (Ama Krushi)

	Year 1	Year 2	Pooled		Year 2
	(1)	(2)	(3)	(4)	(5)
	Adoption index	Adoption index	Yield (Kg/ha)	Harvest (Kg)	Severe crop loss
Treated	0.053	0.119**	41.646	66.972	-0.013
	(0.038)	(0.059)	(41.407)	(52.973)	(0.013)
Treated × Low education index	0.114*	-0.010	5.209	49.040	-0.016
	(0.060)	(0.084)	(59.599)	(78.760)	(0.026)
Low education index	-0.182***	-0.060	-169.250***	-289.612***	0.057***
	(0.052)	(0.066)	(48.993)	(58.979)	(0.016)
N	3399	2398	7431	7431	3893
R-squared	0.018	0.016	0.061	0.371	0.020
Control mean (Low education index)	-0.111	-0.054	2904.042	2117.376	0.246
Control mean (High education index)	0.060	0.036	3141.628	2725.325	0.185
Total effect for low education index	0.167***	0.108*	46.855	116.011*	-0.029
	(0.044)	(0.060)	(42.355)	(62.742)	(0.021)
% of low education index	39.865	42.077	39.241	39.241	39.841

Notes: The analysis reported in this table use the midline and endline survey data from the randomized evaluation of Ama Krushi. The outcome variables are (1) the adoption index at midline, (2) the adoption index at endline, (3) yield (kg/ha) at midline and endline, and (4) harvest (kg) at midline and endline, and (5) severe crop loss reported at endline. For yield and harvest, we pool the midline and endline survey data to estimate the average impact over two years. The education index is created using whether the farmer can read and write, has received any education, and has completed grades 5, 8, or 10. The low education index is a dummy that takes a value of 1 if farmer's education index value is below the panchayat median. Panchayat-year fixed effects are applied. Robust standard errors are reported in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table 7: Heterogeneous treatment impact by wealth level (Ama Krushi)

	Year 1	Year 2	Pooled		Year 2
	(1)	(2)	(3)	(4)	(5)
	Adoption index	Adoption index	Yield (Kg/ha)	Harvest (Kg)	Severe crop loss
Treated	0.078*	0.124**	-36.400	112.820**	0.002
	(0.043)	(0.056)	(41.011)	(55.298)	(0.014)
Treated × Low wealth index	0.042	-0.018	166.711**	-41.515	-0.035
	(0.058)	(0.070)	(64.167)	(82.748)	(0.021)
Low wealth index	-0.025	0.012	-251.600***	-180.592***	0.039**
	(0.045)	(0.049)	(47.328)	(60.408)	(0.018)
N	3377	2389	7379	7379	3873
R-squared	0.015	0.016	0.064	0.370	0.018
Control mean (Low wealth index)	-0.025	-0.016	2879.747	2141.103	0.232
Control mean (High wealth index)	0.020	0.019	3202.121	2746.275	0.181
Total effect for low wealth index	0.121***	0.106*	130.312***	71.305	-0.033**
	(0.039)	(0.055)	(47.399)	(62.757)	(0.016)
% of low wealth index	47.498	47.133	46.700	46.700	46.295

Notes: The analysis reported in this table use the midline and endline survey data from the randomized evaluation of Ama Krushi. The outcome variables are (1) the adoption index at midline, (2) the adoption index at endline, (3) yield (kg/ha) at midline and endline, and (4) harvest (kg) at midline and endline, and (5) severe crop loss reported at endline. For yield and harvest, we pool the midline and endline survey data to estimate the average impact over two years. The wealth index is created using household income from the previous year, whether a farmer's house is constructed entirely with solid materials, and whether it is constructed partially with solid materials. The low wealth index is a dummy that takes a value of 1 if farmer's wealth index value is below the panchayat median. Panchayat-year fixed effects are applied. Robust standard errors are reported in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table 8: Heterogeneous treatment impact by land size (Ama Krushi)

	Year 1	Year 2	Pooled		Year 2
	(1)	(2)	(3)	(4)	(5)
	Adoption index	Adoption index	Yield (Kg/ha)	Harvest (Kg)	Severe crop loss
Treated	0.088**	0.149***	53.401	150.351**	-0.023
	(0.036)	(0.054)	(37.626)	(60.269)	(0.014)
Treated × Small cultivation area	0.017	-0.106	-10.385	-123.166	0.008
	(0.062)	(0.074)	(60.640)	(77.349)	(0.021)
Small cultivation area	-0.180***	-0.082	-112.198**	-731.929***	-0.014
	(0.048)	(0.055)	(44.243)	(70.183)	(0.018)
N	3475	2454	7562	7562	3967
R-squared	0.021	0.021	0.061	0.327	0.016
Control mean (Small cultivation area)	-0.090	-0.048	2993.755	1580.588	0.207
Control mean (Large cultivation area)	0.078	0.038	3088.616	3144.516	0.208
Total effect for small cultivation area	0.104**	0.042	43.016	27.186	-0.016
	(0.048)	(0.055)	(47.594)	(52.338)	(0.016)
% of small cultivation area	44.345	43.521	42.819	42.819	43.055

Notes: The analysis reported in this table use the midline and endline survey data from the randomized evaluation of Ama Krushi. The outcome variables are (1) the adoption index at midline, (2) the adoption index at endline, (3) yield (kg/ha) at midline and endline, and (4) harvest (kg) at midline and endline, and (5) severe crop loss reported at endline. For yield and harvest, we pool the midline and endline survey data to estimate the average impact over two years. Small cultivation area refers to farmers' total crop cultivation area reported at baseline is below the panchayat median. Panchayat-year fixed effects are applied. Robust standard errors are reported in parentheses: * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

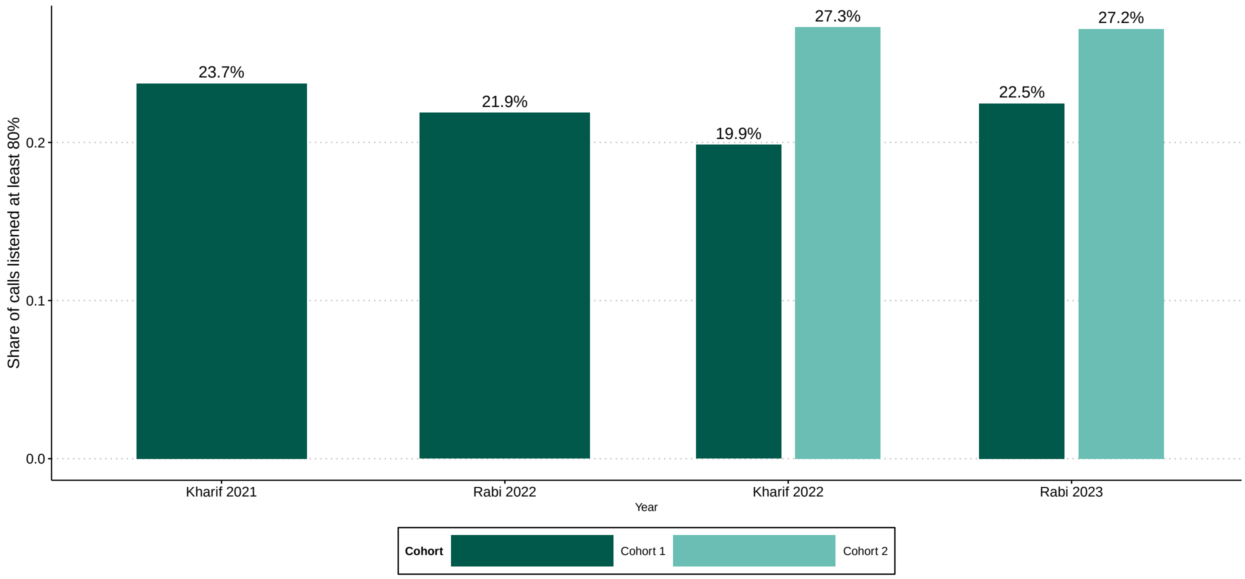
Table 9: Heterogeneous treatment impact by access to infrastructure (Ama Krushi)

	Year 1	Year 2	Pooled		Year 2
	(1)	(2)	(3)	(4)	(5)
	Adoption index	Adoption index	Yield (Kg/ha)	Harvest (Kg)	Severe crop loss
Treated	0.109***	0.120**	9.882	-10.523	-0.015
	(0.038)	(0.049)	(39.292)	(52.458)	(0.013)
Treated × Low infra index	-0.025	-0.041	98.020	251.722***	-0.011
	(0.061)	(0.085)	(61.768)	(88.443)	(0.020)
Low infra index	0.027	-0.027	-69.120	-89.917	0.022
	(0.054)	(0.063)	(56.068)	(59.854)	(0.020)
N	3476	2455	7561	7561	3970
R-squared	0.013	0.015	0.059	0.369	0.016
Control mean (Low infra index)	0.002	-0.032	3015.316	2497.657	0.217
Control mean (High infra index)	-0.001	0.023	3073.857	2450.902	0.201
Total effect for low infra index	0.085*	0.079	107.902**	241.199***	-0.026*
	(0.047)	(0.068)	(48.387)	(70.505)	(0.015)
% of low infra index	40.420	40.285	40.735	40.735	40.327

Notes: The analysis reported in this table use the midline and endline survey data from the randomized evaluation of Ama Krushi. The outcome variables are (1) the adoption index at midline, (2) the adoption index at endline, (3) yield (kg/ha) at midline and endline, and (4) harvest (kg) at midline and endline, and (5) severe crop loss reported at endline. For yield and harvest, we pool the midline and endline survey data to estimate the average impact over two years. The village-level infrastructure index is created using whether the village has paved roads, a post office, a bank, a computer center, a health clinic, and a secondary school. The low infrastructure index is a dummy that takes a value of 1 if the farmer's infrastructure index value is below the panchayat median. Standard errors are clustered at the village level and reported in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

6.2 Figures

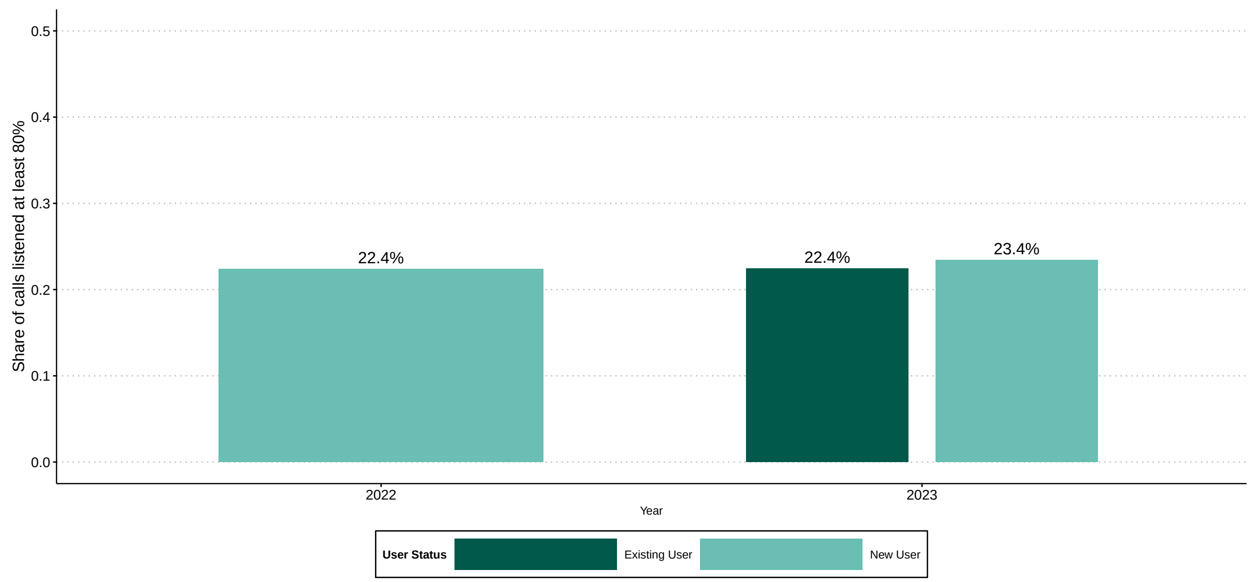
Figure 1: Engagement trends by agricultural season (Ama Krushi)



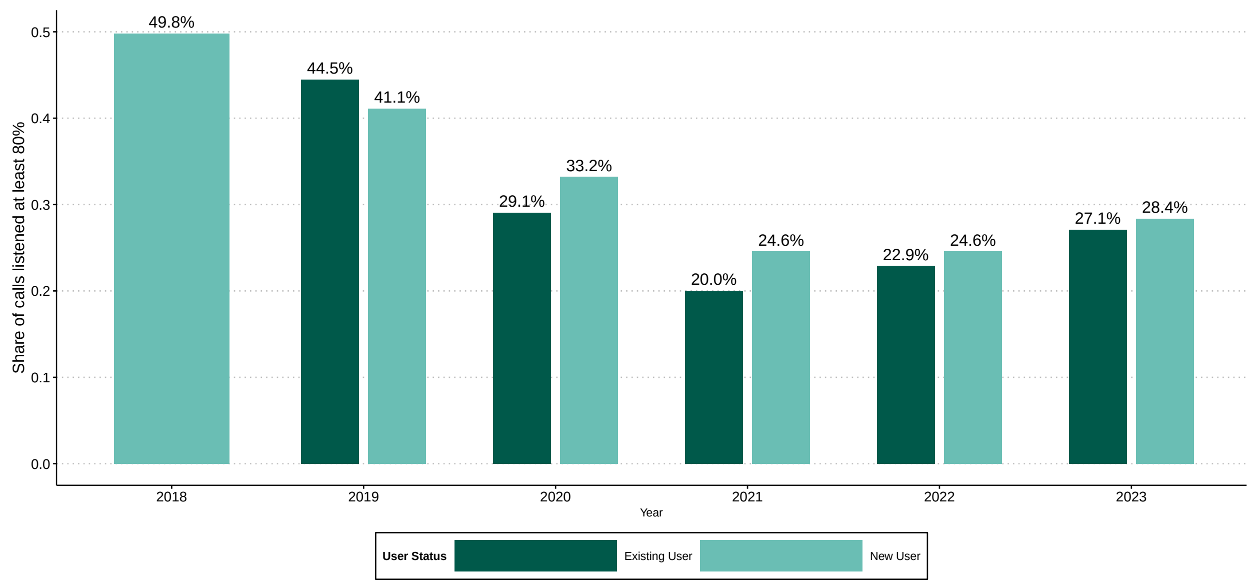
Notes: These figures are generated using PxD's administrative data from Ama Krushi. They show the share of advisory calls of which farmers listened to at least 80% content over different agricultural seasons, by cohort.

Figure 2: Engagement trends by calendar year (Coffee Krishi Taranga)

a. Andhra Pradesh

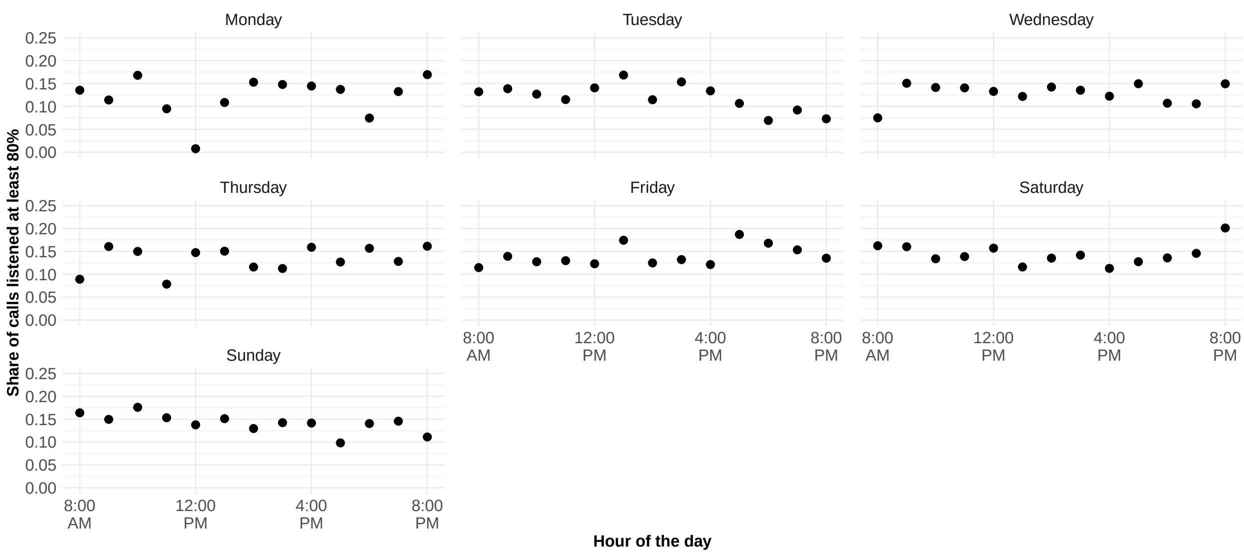


b. Karnataka and Kerala and Tamil Nadu



Notes: These figures are generated using PxD's administrative data from Coffee Krishi Taranga. The sample is restricted to farmers who have been profiled and excludes 31% of advisory calls with missing information on call length. They show the shares of advisory calls of which farmers listened to at least 80% content over different calendar years, by user status. New users are farmers who have been profiled less than 1 year.

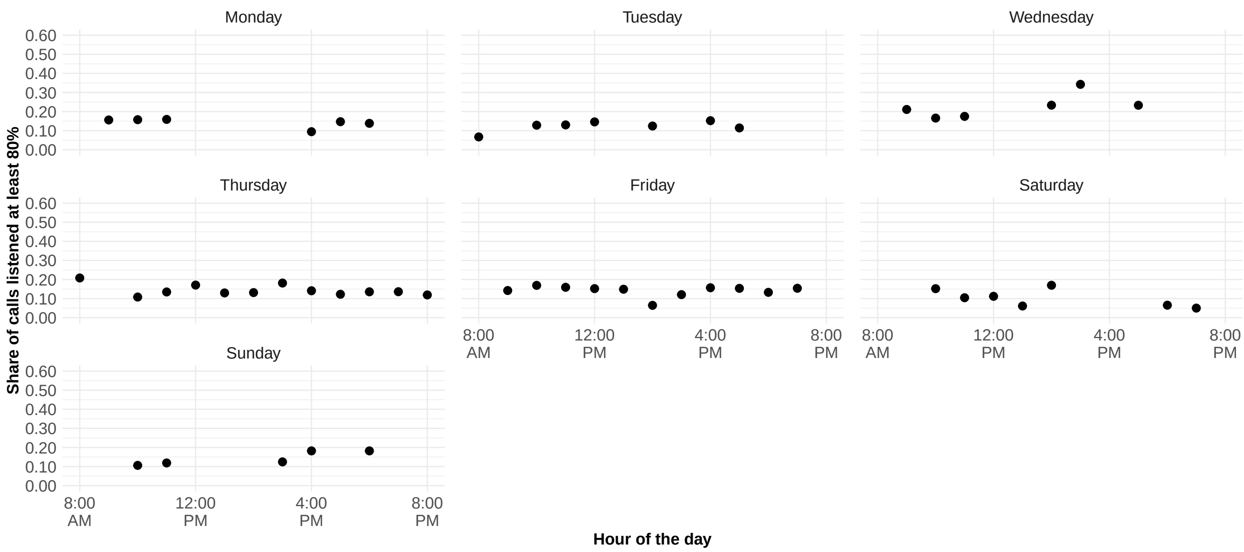
Figure 3: Engagement trends by hour and day of the week (Ama Krushi)



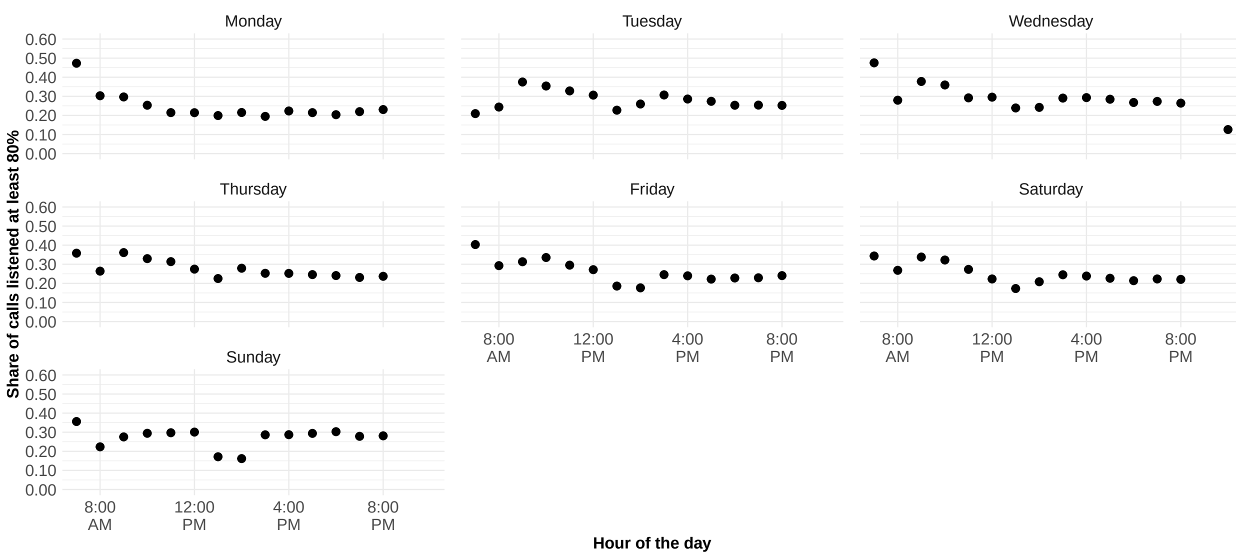
Notes: These figures are generated using PxD's administrative data from Ama Krushi. Day-hour blocks that had less than 100 advisory calls are excluded from the analysis. They show the shares of advisory calls of which farmers listened to at least 80% content over different days of the week and hours of the day. The average listening rates are 0.12, 0.10, 0.14, 0.14, 0.15, 0.14, and 0.14 for Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday, respectively.

Figure 4: Engagement trends by hour and day of the week (Coffee Krishi Taranga)

a. Andhra Pradesh

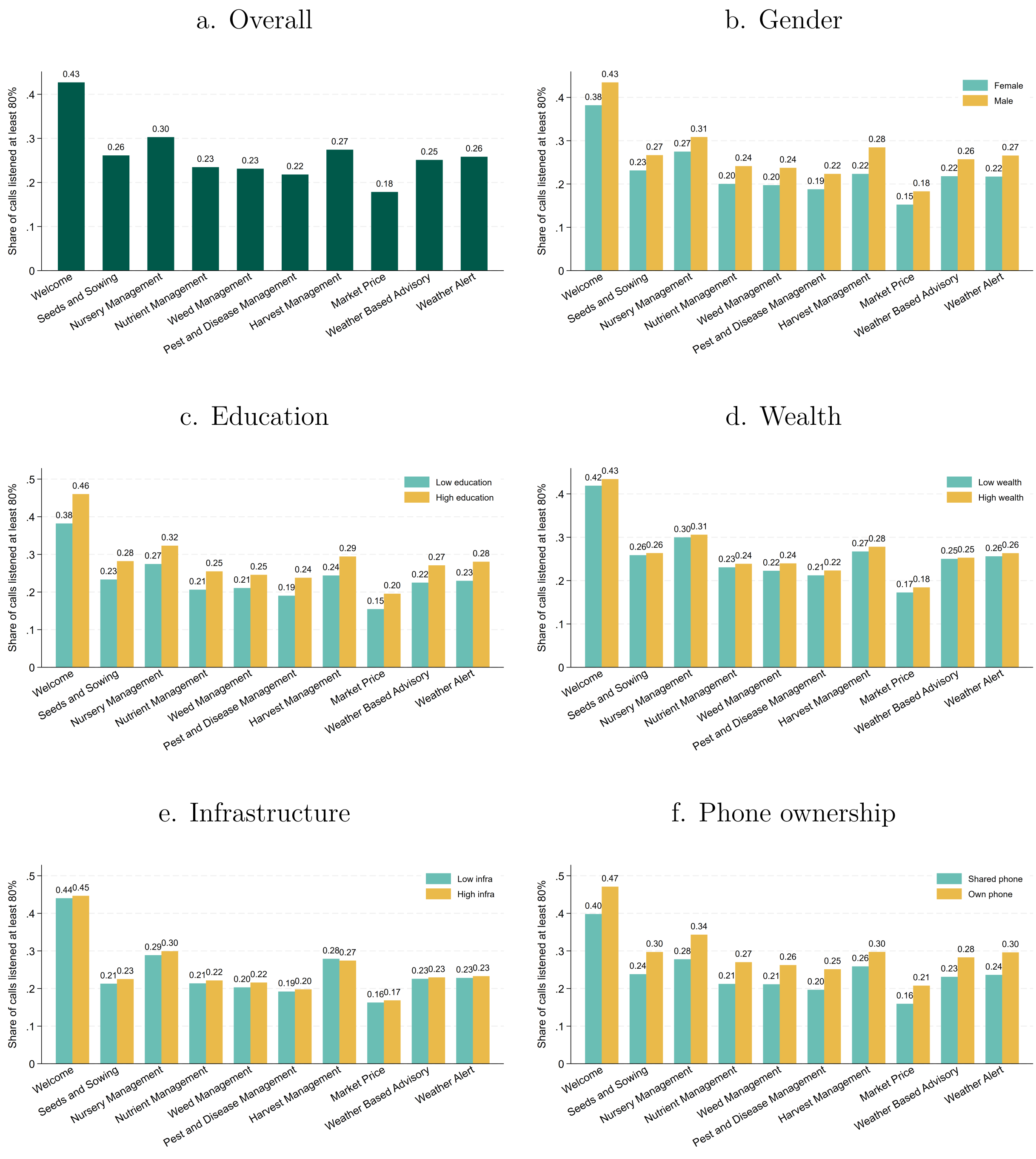


b. Karnataka and Kerala and Tamil Nadu



Notes: These figures are generated using PxD's administrative data from Coffee Krishi Taranga. The sample is restricted to farmers who have been profiled and excludes 31% of advisory calls with missing information on call length. Day-hour blocks that had less than 100 advisory calls are excluded from the analysis. They show the shares of advisory calls of which farmers listened to at least 80% content over different days of the week and hours of the day. The average listening rates are 0.24, 0.31, 0.31, 0.31, 0.28, 0.26, and 0.27 for Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday, respectively.

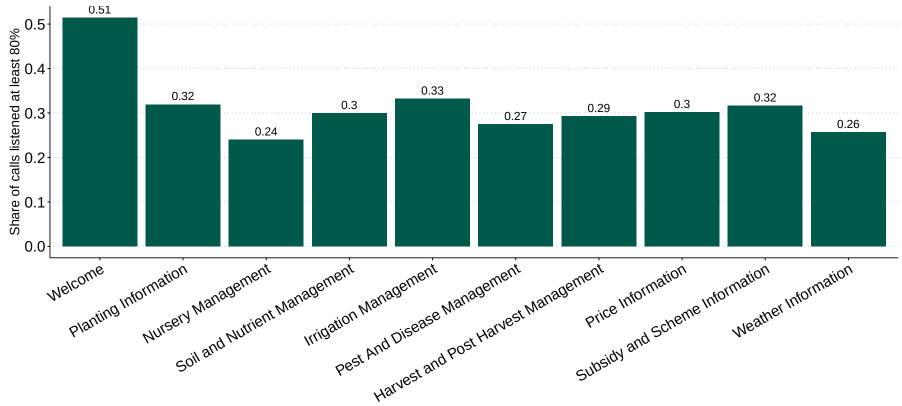
Figure 5: Engagement by advisory topic (Ama Krushi)



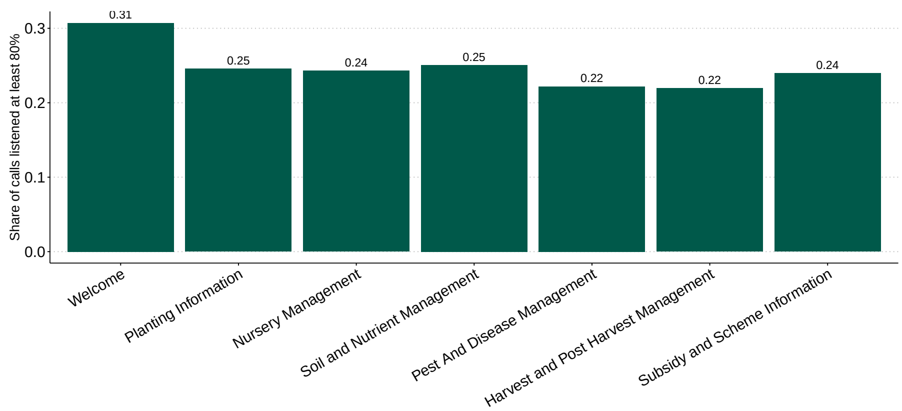
Notes: These figures are generated using PxD's administrative data from Ama Krushi. They show the shares of advisory calls of which farmers listened to at least 80% content by advisory topic.

Figure 6: Engagement by advisory topic, overall pattern (Coffee Krishi Taranga)

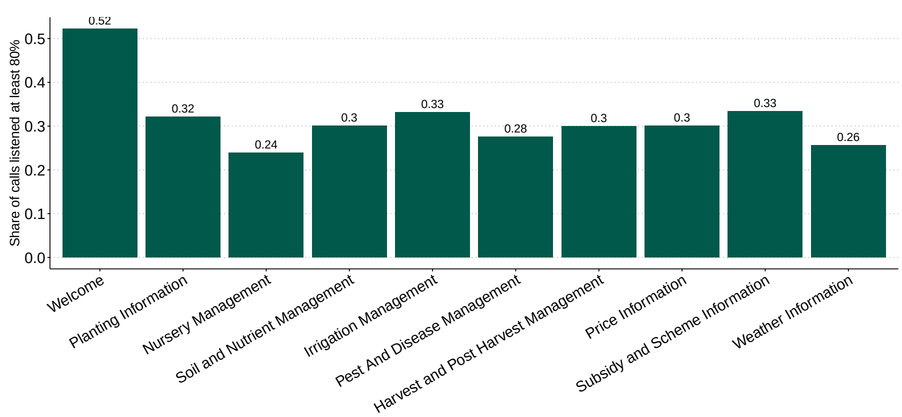
a. Full sample



b. Andhra Pradesh



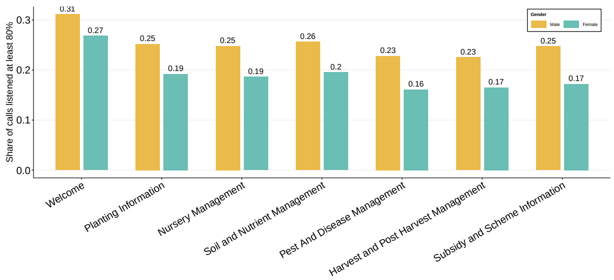
c. Karnataka and Kerala and Tamil Nadu



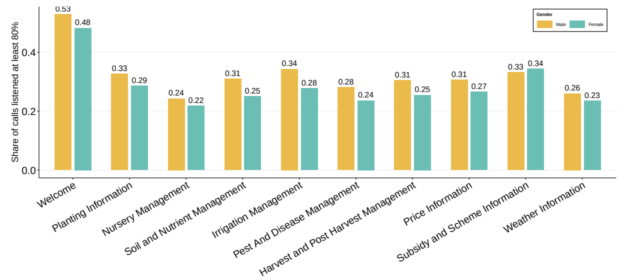
Notes: These figures are generated using PxD's administrative data from Coffee Krishi Taranga. The sample is restricted to farmers who have been profiled and excludes 31% of advisory calls with missing information on call length. They show the shares of advisory calls of which farmers listened to at least 80% content by advisory topic.

Figure 7: Engagement by advisory topic, by farmer characteristics (Coffee Krishi Taranga)

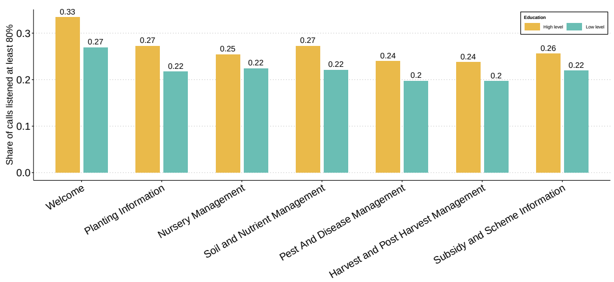
a. Gender: AP



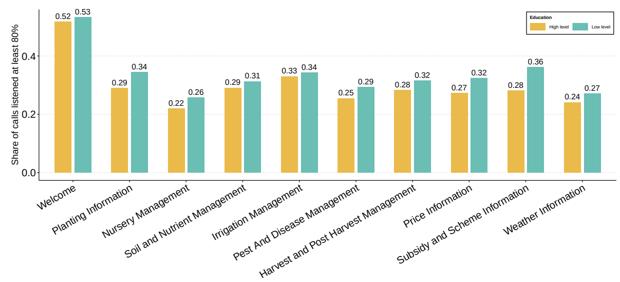
b. Gender: KA & KL & TN



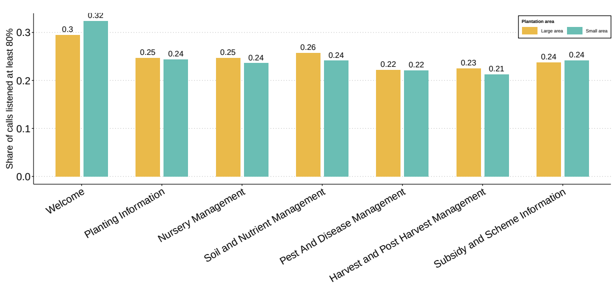
c. Education: AP



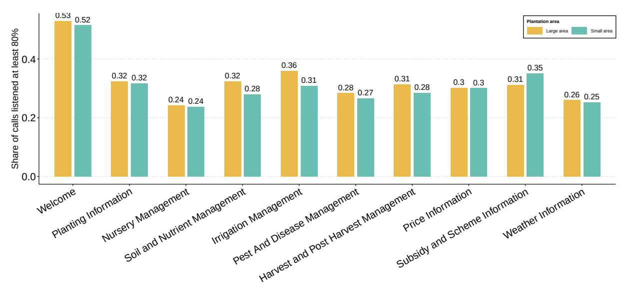
d. Education: KA & KL & TN



e. Land: AP



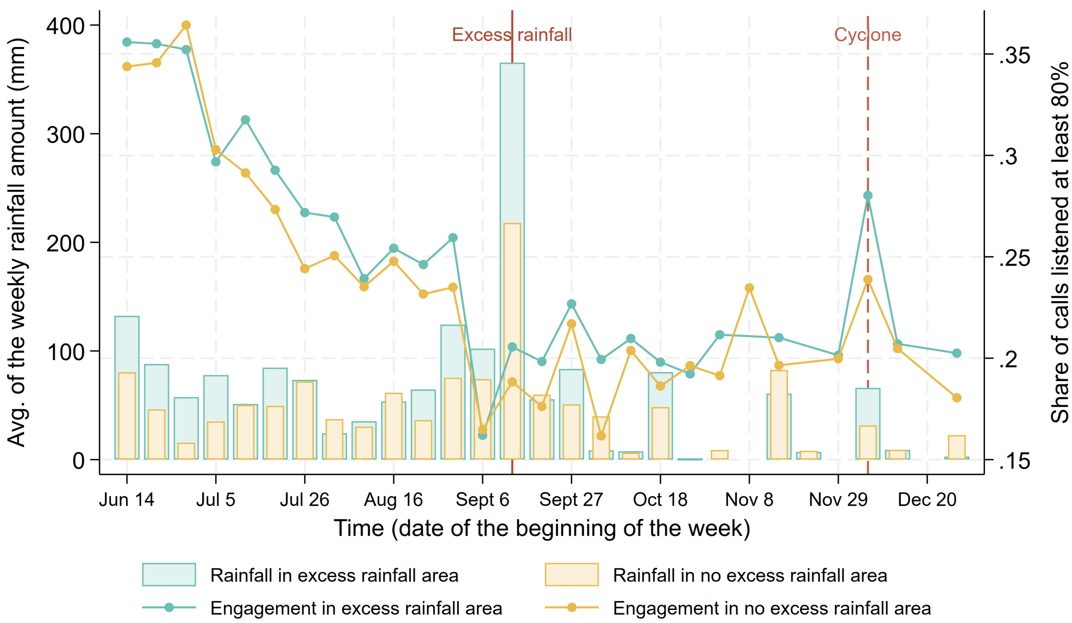
f. Land: KA & KL & TN



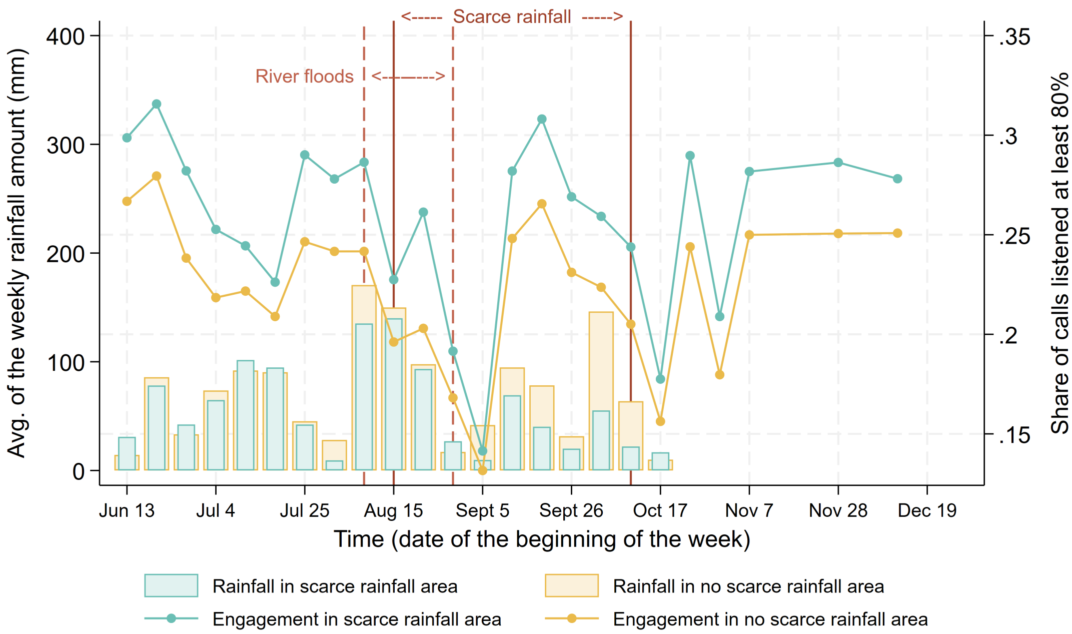
Notes: These figures are generated using PxD's administrative data from Coffee Krishi Taranga. The sample is restricted to farmers who have been profiled and excludes 31% of advisory calls with missing information on call length. They show the shares of advisory calls of which farmers listened to at least 80% content over each advisory topic, by farmers' characteristics.

Figure 8: Engagement patterns (listened ≥ 80%) over weather realizations (Ama Krushi)

a. Kharif 2021



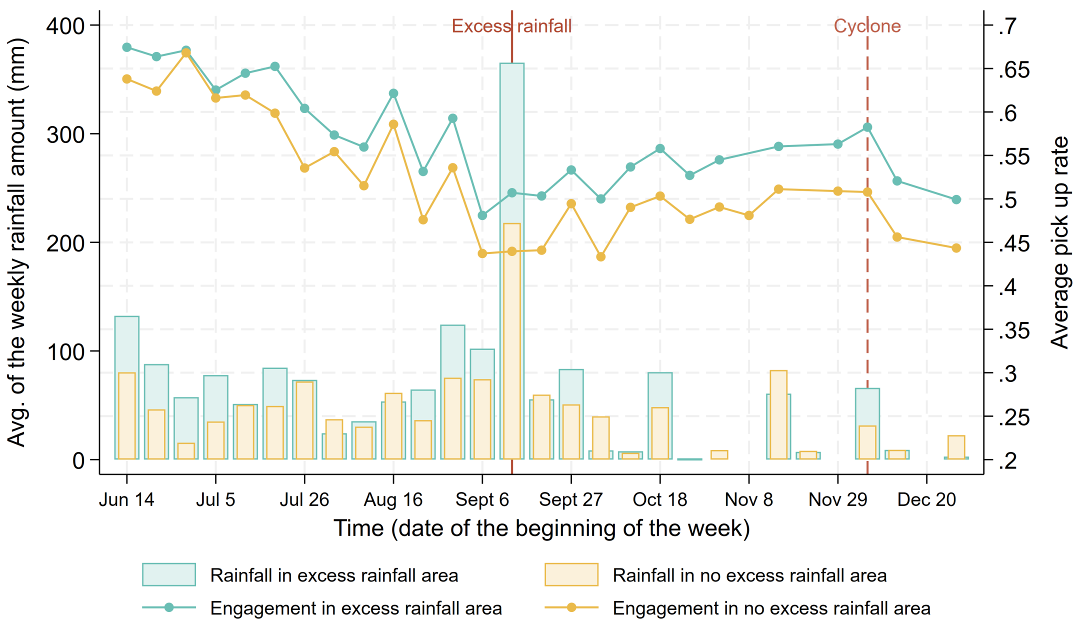
b. Kharif 2022



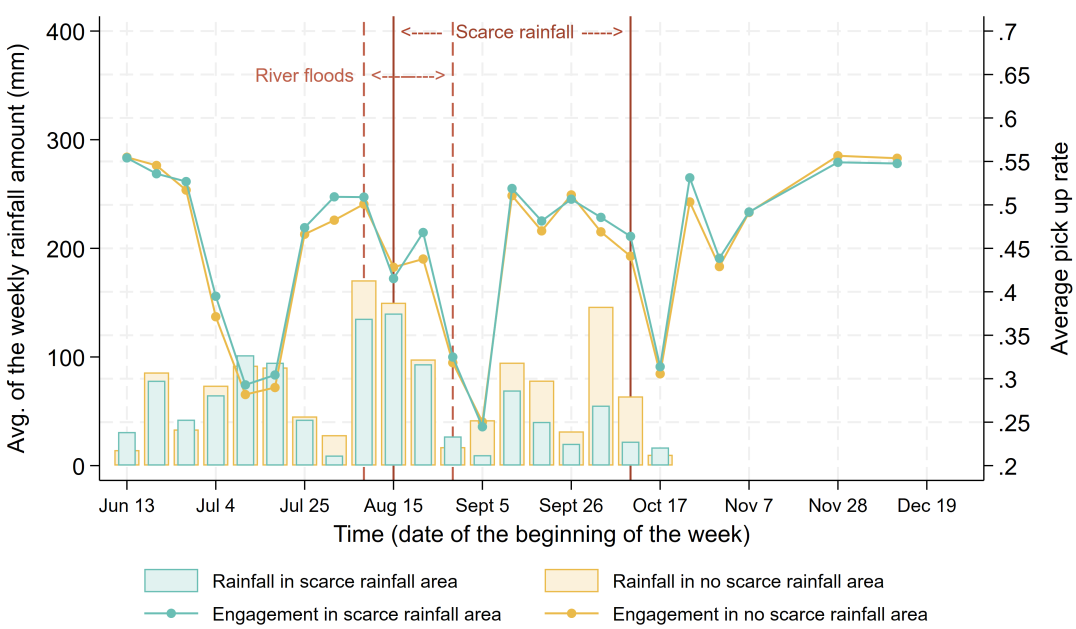
Notes: These figures are generated using PxD's administrative data from Ama Krushi and public weather data. Each bar represents the average weekly rainfall amounts over all blocks in areas with or without weather shocks. Each line represents the proportion of calls listened at least 80% out of all calls sent during that week, in areas with or without weather shocks. Weather shocks are defined as follows: "excess rainfall" area refers to blocks received more than 250 mm rainfall over two days in the period of August 16 to October 15 in 2021; "cyclone" refers to blocks received more than 50 mm rainfall over two days in the period of December 4 to December 10 in 2021; "river floods" refers to panchayats experienced river flooding in August 2022; and "scarce rainfall" area refers to blocks received less than 450 mm rainfall over the period of August 16 to October 15 in 2022.

Figure 9: Engagement patterns (pick-up rate) over weather realizations (Ama Krushi)

a. Kharif 2021



b. Kharif 2022



Notes: These figures are generated using PxD's administrative data from Ama Krushi and public weather data. Each bar represents the average weekly rainfall amounts over all blocks in areas with or without weather shocks. Each line represents the average pick-up rate among all calls sent during that week, in areas with or without weather shocks. Weather shocks are defined as follows: "excess rainfall" area refers to blocks received more than 250 mm rainfall over two days in the period of August 16 to October 15 in 2021; "cyclone" refers to blocks received more than 50 mm rainfall over two days in the period of December 4 to December 10 in 2021; "river floods" refers to panchayats experienced river flooding in August 2022; and "scarce rainfall" area refers to blocks received less than 450 mm rainfall over the period of August 16 to October 15 in 2022.

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Appendix

A Additional Tables and Figures

Table A1: Correlation between farmer characteristics and any service usage
[Outcome: Indicator for whether a farmer listened to at least one advisory call in a given season]
(Ama Krushi)

	1st year of enrollment		2nd year of enrollment	
	(1) in Kharif	(2) in Rabi	(3) in Kharif	(4) in Rabi
Age	0.001*	0.001*	0.003***	0.002**
	(0.000)	(0.001)	(0.001)	(0.001)
Female	0.010	-0.001	0.002	0.000
	(0.010)	(0.019)	(0.023)	(0.028)
Joined decision making	0.005	-0.013	0.004	-0.007
	(0.006)	(0.012)	(0.016)	(0.021)
Low edudcaion index	-0.020***	-0.060***	-0.025*	-0.034*
	(0.006)	(0.011)	(0.015)	(0.019)
Low wealth index	-0.002	-0.027**	-0.004	-0.047**
	(0.006)	(0.011)	(0.014)	(0.019)
Small cultivation area	-0.001	0.004	-0.006	0.013
	(0.006)	(0.011)	(0.015)	(0.019)
Low infrastructure index	-0.012	-0.007	-0.014	-0.012
	(0.009)	(0.019)	(0.015)	(0.019)
Primary phone: shared regularly	-0.022***	-0.051***	-0.051***	-0.077***
	(0.006)	(0.011)	(0.015)	(0.019)
Primary phone: feature phone	-0.007	0.026**	-0.033**	-0.015
	(0.006)	(0.011)	(0.015)	(0.019)
Have access to irrigation	-0.000	0.046***	0.026*	0.046**
	(0.006)	(0.011)	(0.016)	(0.020)
Adverse rainfall shock in the pervious year	0.007	0.015	-0.015	-0.002
	(0.006)	(0.012)	(0.019)	(0.025)
N	5758	5727	2086	2098
R^2	0.010	0.033	0.019	0.033
Average	0.953	0.796	0.882	0.782

Notes: Data are from PxD's administrative data of the Ama Krushi service. The dependent variables are whether farmers picked up at least one advisory call in the 1st, 2nd, 3rd, and 4th agricultural seasons since enrolled with the service, respectively. All regressions additionally control for the cohort dummy and district dummies. Robust standard errors are reported in parenthesis: * p<0.10, ** p<0.05, *** p<0.01.

Table A2: Correlation between farmer characteristics and any service usage
[Outcome: Indicator for whether a farmer listened to at least one advisory call in a given year]
(Coffee Krishi Taranga)

	Andhra Pradesh		Karnataka & Kerala & Tamil Nadu			
	(1)	(2)	(3)	(4)	(5)	(6)
	1st year	2nd year	1st year	2nd year	3rd year	4th year
Age	-0.002***	0.000	0.000***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.048***	-0.043	-0.009***	-0.023***	-0.040***	-0.038***
	(0.017)	(0.031)	(0.002)	(0.003)	(0.006)	(0.013)
Low education	-0.068***	-0.042**	-0.002	0.008***	0.017***	0.039***
	(0.012)	(0.019)	(0.001)	(0.002)	(0.004)	(0.008)
Small coffee land	(0.012)	(0.019)	0.000	0.003	0.000	-0.010
	(0.010)	(0.016)	(0.001)	(0.002)	(0.004)	(0.008)
Has functioning irrigation	0.049	-0.018	0.000	0.007***	0.001	-0.006
	(0.031)	(0.062)	(0.001)	(0.002)	(0.004)	(0.008)
Uses any fertilizer	0.134***	-0.025	-0.085**	-0.021***	-0.042***	0.311***
	(0.011)	(0.023)	(0.036)	(0.008)	(0.016)	(0.077)
Intercropping	-0.117***	0.003	0.002	0.003	0.014	-0.040**
	(0.010)	(0.018)	(0.003)	(0.005)	(0.009)	(0.017)
Feature phone			-0.002	0.001	-0.004	-0.020**
			(0.001)	(0.002)	(0.004)	(0.008)
Num. Observations	5419	2526	73049	64456	35947	10467
Mean of Outcome	0.824	0.809	0.973	0.930	0.879	0.737

Notes: Data are from PxD's administrative data of the Coffee Krishi Taranga service, restricting the sample to farmers who have been profiled and advisory calls that have information on their length. The dependent variables are whether farmers picked up at least one advisory call in the 1st, 2nd, 3rd, and 4th year since enrolled with the service, respectively. Additional controls include missing dummies for each covariate that indicate missing values are imputed with the median value within the state. District-level fixed effects are included. Robust standard errors are reported in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table A3: Balance checks of baseline characteristics (Key characteristics)

	(1) Adoption Index	(2) Yield (Kg/ha)	(3) Harvest (Kg)
Panel A: Education index			
Treated	-0.025	-7.013	-37.211
	(0.061)	(43.663)	(45.337)
Treated × Low edudcaion index	0.095	19.160	26.016
	(0.079)	(80.163)	(78.340)
Low education index	-0.178***	-113.694*	-144.129**
	(0.060)	(62.507)	(62.459)
N	2042	4741	4741
Control mean (High education index)	0.088	3097.282	2334.080
Panel B: Household wealth index			
Treated	-0.004	-52.078	-47.920
	(0.063)	(62.770)	(53.697)
Treated × Low wealth index	0.078	107.761	44.344
	(0.094)	(95.043)	(68.195)
Low wealth index	-0.093	-146.113**	-193.738***
	(0.060)	(67.870)	(56.004)
N	2028	4714	4714
Control mean (High wealth index)	0.047	3168.193	2432.965
Panel C: Total cultivation area			
Treated	0.031	-64.315	-67.127
	(0.053)	(53.059)	(64.606)
Treated × Small cultivation area	-0.030	149.069*	60.178
	(0.080)	(84.881)	(76.873)
Small cultivation area	-0.101*	502.629***	-1458.868***
	(0.058)	(62.135)	(70.635)
N	2087	4829	4829
Control mean (Large cultivation area)	0.043	2827.339	2825.568
Panel D: Village infrastructure index			
Treated	-0.016	-1.941	-4.406
	(0.055)	(52.092)	(46.137)
Treated × Low infra index	0.100	4.787	-54.681
	(0.087)	(85.906)	(79.087)
Low infra index	-0.064	52.348	53.627
	(0.070)	(78.117)	(64.840)
N	2087	4834	4834
Control mean (High infra index)	0.024	3046.075	2101.608

Notes: Data are from the baseline survey of the randomized evaluation. The outcome variables are (1) the adoption index, (2) yield (kg/ha), and (3) harvest (kg). Panchayat fixed effects are included. Standard errors are clustered at the village level for the infrastructure panel and robust for other panels, reported in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table A4: Balance checks of baseline characteristics (Gender perspective)

	(1) Adoption Index	(2) Yield (Kg/ha)	(3) Harvest (Kg)
Panel A: Gender			
Treated	0.016	-36.124	-65.901
	(0.044)	(47.155)	(48.014)
Treated × Female	0.047	208.413**	234.924**
	(0.087)	(91.669)	(88.566)
Female	-0.015	-188.157**	-265.962***
	(0.071)	(73.962)	(82.493)
N	2090	4839	4839
Control mean (Male)	0.039	2971.481	2228.624
Panel B: Joint decision making on paddy farming			
Treated	-0.085	-15.789	-41.641
	(0.058)	(54.967)	(60.034)
Treated × Joint decision making	0.167**	23.349	26.571
	(0.073)	(83.888)	(82.469)
Joint decision making	0.004	22.268	8.460
	(0.071)	(73.214)	(68.293)
N	1904	4408	4408
Control mean (Solo decision making)	0.151	2890.581	2218.353

Notes: Data are from the baseline survey of the randomized evaluation. The outcome variables are (1) the adoption index, (2) yield (kg/ha), and (3) harvest (kg). Panchayat fixed effects are included. Robust standard errors are reported in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table A5: Heterogeneous treatment impact by gender (Ama Krushi)

	Year 1	Year 2	Pooled		Year 2
	(1)	(2)	(3)	(4)	(5)
	Adoption index	Adoption index	Yield (Kg/ha)	Harvest (Kg)	Severe crop loss
Treated	0.105***	0.136***	40.564	82.576*	-0.009
	(0.028)	(0.044)	(32.357)	(44.663)	(0.011)
Treated × Female	-0.028	-0.146*	64.976	73.221	-0.063*
	(0.067)	(0.074)	(77.613)	(93.235)	(0.035)
Female	-0.024	0.073	-244.579***	-472.576***	0.101***
	(0.052)	(0.061)	(63.353)	(69.272)	(0.022)
N	3479	2457	7568	7568	3973
R-squared	0.013	0.016	0.062	0.373	0.021
Control mean (Female)	-0.015	-0.091	3067.270	1770.163	0.225
Control mean (Male)	0.003	0.025	3043.419	2601.060	0.204
Total effect for female	0.077	-0.010	105.540	155.796*	-0.073**
	(0.067)	(0.069)	(70.733)	(86.892)	(0.033)
% of female	19.086	21.408	16.173	16.173	17.946

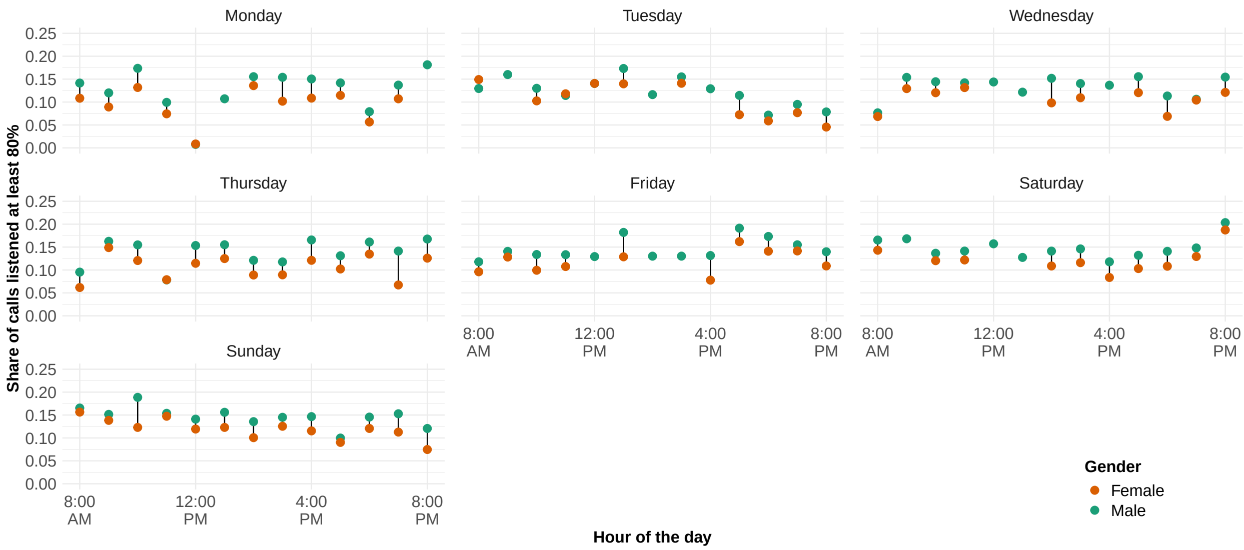
Notes: Data are from the midline and endline survey of the randomized evaluation. The outcome variables are (1) the adoption index from the midline survey, (2) adoption index from the endline survey, (3) yield (kg/ha) are pooled from the midline and endline survey, and (4) harvest (kg) are pooled from the midline and endline survey and (5) severe crop loss from the endline survey. The treatment variable is a dummy that takes a value of 1 if the farmer belongs to the treatment group. The female variable is a dummy that takes a value of 1 if the farmer is female. Robust standard errors are reported in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Table A6: Heterogeneous treatment impact by joint decision-making (Ama Krushi)

	Year 1	Year 2	Pooled		Year 2
	(1)	(2)	(3)	(4)	(5)
	Adoption index	Adoption index	Yield (Kg/ha)	Harvest (Kg)	Severe crop loss
Treated	0.168***	0.150**	47.126	109.408*	0.009
	(0.038)	(0.058)	(43.639)	(59.042)	(0.015)
Treated × Joint decision making	-0.122**	-0.056	10.542	-11.152	-0.057**
	(0.059)	(0.073)	(59.938)	(80.351)	(0.022)
Joint decision making	0.139***	0.092	-73.734	-105.395*	0.050***
	(0.050)	(0.060)	(51.804)	(61.778)	(0.016)
N	3174	2252	6939	6939	3638
R-squared	0.018	0.019	0.063	0.368	0.018
Control mean (Solo decision making)	-0.006	-0.039	3053.114	2299.094	0.194
Control mean (Joint decision making)	-0.002	0.062	3062.098	2628.933	0.217
Total effect for joint decision making	0.047	0.094*	57.668	98.256*	-0.048***
	(0.042)	(0.050)	(43.705)	(57.915)	(0.016)
% of joint decision making	49.338	51.909	46.736	46.736	48.708

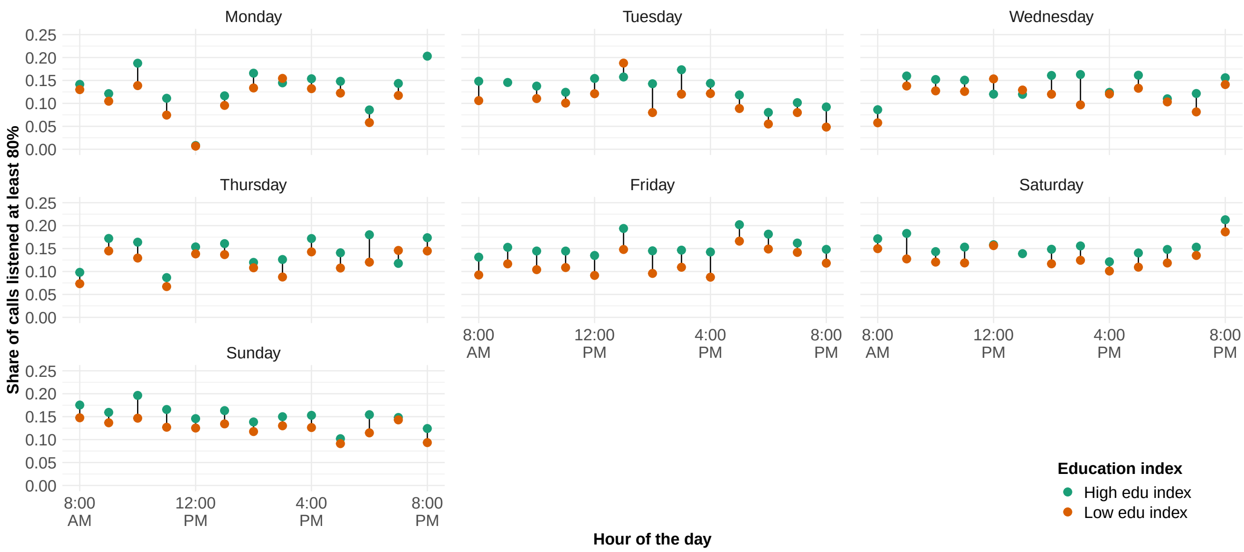
Notes: Data are from the midline and endline survey of the randomized evaluation. The outcome variables are (1) the adoption index from the midline survey, (2) adoption index from the endline survey, (3) yield (kg/ha) are pooled from the midline and endline survey, and (4) harvest (kg) are pooled from the midline and endline survey and (5) severe crop loss from the endline survey. The treatment variable is a dummy that takes a value of 1 if the farmer belongs to the treatment group. The joint decision making variable is a dummy that takes a value of 1 if spouse contributes to decision making about paddy cultivation. Robust standard errors are reported in parentheses: * p<0.10, ** p<0.05, *** p<0.01.

Figure A1: Time trends in engagement by hour and day of the week, by gender (Ama Krushi)



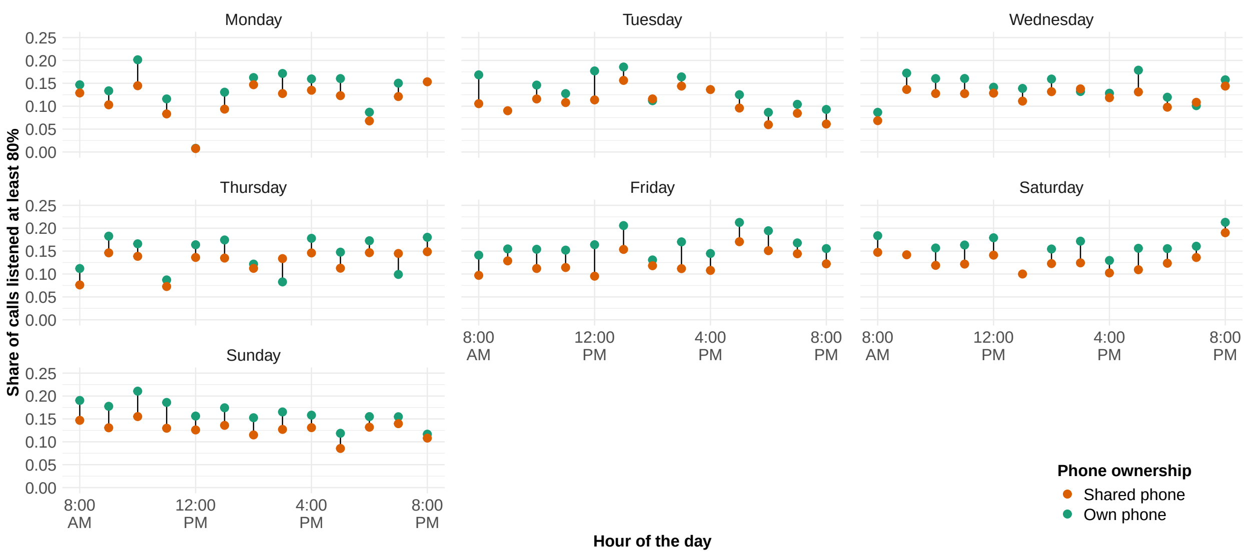
Notes: These figures are generated using PxD's administrative data of the Ama Krushi service. Character-day-hour blocks that had less than 100 calls are excluded from the analysis. They show the share of advisory calls that farmers listened to at least 80% content over different days of the week and hours of the day, separately by farmer characteristics. The average listening rates are 0.12, 0.10, 0.14, 0.14, 0.15, 0.14, and 0.14 for Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday, respectively.

Figure A2: Time trends in engagement by hour and day of the week, by eduction level (Ama Krushi)



Notes: These figures are generated using PxD's administrative data of the Ama Krushi service. Character-day-hour blocks that had less than 100 calls are excluded from the analysis. They show the share of advisory calls that farmers listened to at least 80% content over different days of the week and hours of the day, separately by farmer characteristics. The average listening rates are 0.12, 0.10, 0.14, 0.14, 0.15, 0.14, and 0.14 for Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday, respectively.

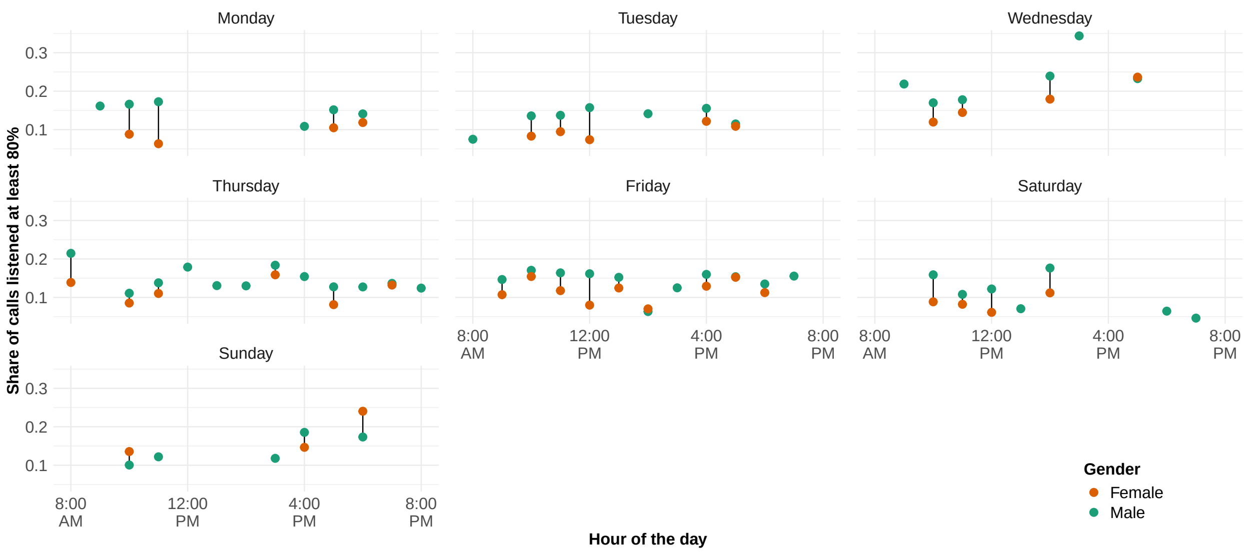
Figure A3: Time trends in engagement by hour and day of the week, by phone ownership (Ama Krushi)



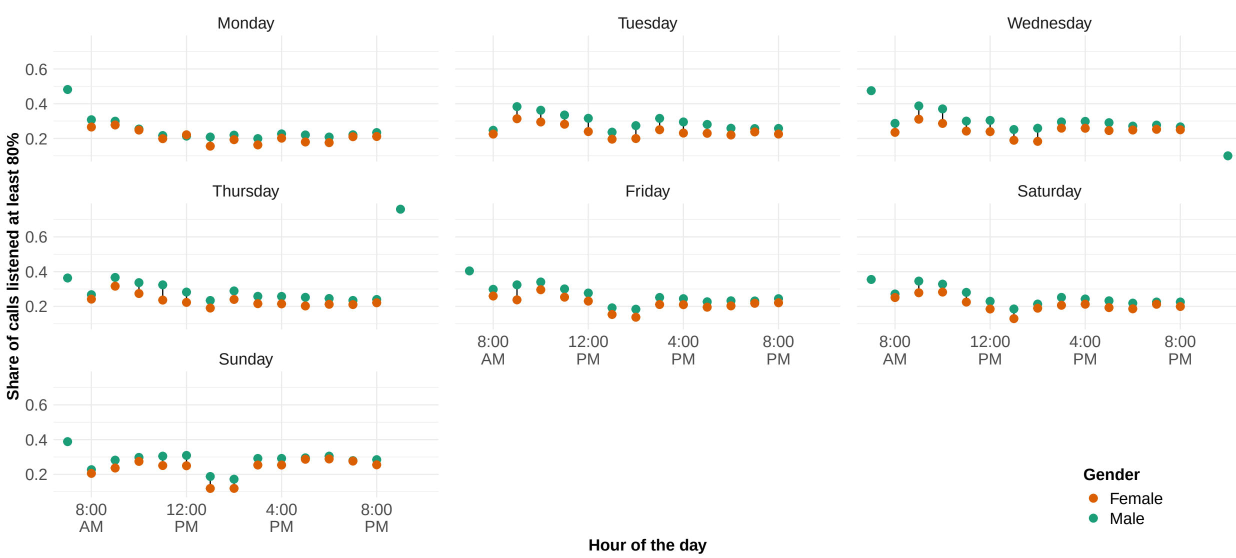
Notes: These figures are generated using PxD's administrative data of the Ama Krushi service. Character-day-hour blocks that had less than 100 calls are excluded from the analysis. They show the share of advisory calls that farmers listened to at least 80% content over different days of the week and hours of the day, separately by farmer characteristics. The average listening rates are 0.12, 0.10, 0.14, 0.14, 0.15, 0.14, and 0.14 for Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday, respectively.

Figure A4: Time trends in engagement by hour and day of the week, by gender (Coffee Krishi Taranga)

a. Andhra Pradesh



b. Karnataka and Kerala and Tamil Nadu



Notes: These figures are generated using PxD's administrative data of the Coffee Krishi Taranga service, restricting the sample to farmers who have been profiled and advisory calls that have information on their length. Gender-day-hour blocks that had less than 100 advisory calls are excluded from the analysis. They show the share of advisory calls that farmers listened to at least 80% content over different days of the week and hours of the day. The average listening rates are 0.24, 0.31, 0.31, 0.31, 0.28, 0.26, and 0.27 for Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, and Sunday, respectively.