# Scaling Up Peer Education with Farmers in India*

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## ABSTRACT

Researchers and agricultural advisory services often use data-driven approaches to target content to farmers. We demonstrate that allowing farmers to direct targeting procedures on their own is a more efficient way of scaling educational content than targeting based on demographic and agronomic indicators. Within the Khedut Saathi mobile message forwarding system, farmers received audio content on their phones, and could anonymously forward messages to up to five other phone numbers. Using Ordinary Least Squares regressions, we find that relative to targeting based on simple demographic and agronomic indicators, farmers are significantly more effective in identifying and targeting farmers most likely to be interested in messages – based on how long farmers listen, and how likely they are to listen to complete messages before hanging up. Significant volumes of incoming calls were also made to our service from unrecognized phone numbers, implying a diffusion of the service offline by farmers. These results demonstrate the importance of farmers' own social connections for targeting and scaling educational content.

## CCS CONCEPTS

• **Human centered computing** → **Field Studies**; *Social media*; Empirical studies in HCI.

## KEYWORDS

Information targeting, peer targeting, precision agriculture.

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## 1 INTRODUCTION

When exploring disseminating educational content to the millions of small-scale rural farmers in developing countries who are currently underserved by traditional agricultural extension services, researchers often focus on how well data-driven approaches can be used to know which farmers to target. Using data to target farmers to adopt fertilizer may work by focusing on farmers' behavioral limitations. [1–2]. Data from sources such as censuses of visible assets or community wealth-based rankings have also been similarly used to identify and target particularly needy farmers [3]. However, the significant difficulties of knowing in advance which farmers are most likely to be interested in new content may mean unnecessarily high costs in collecting data about farmers. Such expenses include the costs of creating and sending messages to farmers who ultimately have little interest, while ignoring farmers who urgently need the new content. These are costs few agricultural ministries, agencies and smaller organizations can afford.

With a focus on using data and technology to empower farmers, recent research has made creative and diverse strides for policy, such as using mobile money transfers to facilitate investments in agriculture [4], using mobile phone metadata to predict poverty levels [5] and harnessing satellite imagery to efficiently delineate large farming areas of policy interest [6]. However, the data used by such tools often ignores the intuitions of the participants themselves in terms of knowing who to target. In existing farmer networks, some farmers may adjust their inputs to correspond with those of their colleagues who were unexpectedly successful in previous periods [7]. Yet, farmers have little to no agency in knowledge-scaling beyond consuming the information provided in such settings, and from sharing the information by word-of-mouth in an ad-hoc manner. A strong literature in offline peer-driven learning and farmer field schooling [8-11] suggests that farmers benefit from horizontal knowledge sharing, although the question of how to scale such educational content using technology remains unclear.

In this paper, we contribute a methodology for efficiently targeting farmers that are most likely to listen to mobile educational content. We rely on farmers to intuitively target their peers, and compare their efficiency with a data-driven approach. Taking a page from social media platforms, which commonly allow peers to forward relevant messages to one another, we analyze a voice-based social media platform called Khedut Saathi (meaning "Farmer's Friend") where farmers are able to forward voice messages to one another. Khedut Saathi allows its users to forward messages to up to five other farmers who might benefit from such content, by entering the phone numbers of would-be receivers. This forwarding feature is free of charge for both the sender and the receiver.

In our study, the farmers who receive forwarded messages from other farmers are blinded from knowing who actually sent them the content, and do not see the phone numbers of the forwarders. Since the farmers who receive forwarded messages have no way of telling who sent the message to them, such receiver farmers are essentially the subjects of forwarder "experiments"–where farmers organically transmit messages through other farmers anonymously.

We observe the degree to which farmers interact with and listen to messages – both when they are selected randomly, as well as targeted by another farmer. We find that peer messaging significantly predicts the degree to which farmers listen to content that these effects are more significant than messaging based on simple demographic and agronomic indicators. We also find that farmers who receive messages from peers are more likely to listen to an entire message before hanging up, relative to data-generated farmers. This shows that farmers have a strong intuition for predicting and identifying farmers who are most likely to consume content. The findings suggest that peer-based targeting has strong potential for fostering learning in the technology for agricultural development space.

### 1.1 Related Literature

A multidisciplinary body of work has studied the complex role of information in agricultural development. In the information technology for development literature, Aker et al observe that although farmers have significant ongoing needs for timely and low-cost information services, there is a mixed record in terms of adopting such mobile services and consuming new content [12]. Recent work in sociology shows that the value of mobile technologies is linked to the enhancement of existing social relationships [13], and that offline relationships are critical to the success of such programs [14-18].

Our work contributes to such discussions by quantifying the ability of farmers to target and identify other farmers that are most likely to consume new information. We compare farmer-led targeting to simple data-driven targeting using the socioeconomic characteristics of farmers. As such, our paper builds on the international development literature, which uses a variety of data-driven approaches to target poor people with new information or other resources. For example, researchers have assessed targeting mechanisms using microfinance indicators [19], marketing campaigns [20], mobile money records [4], satellite imagery [6] or mobile phone meta-data [5]. Our focus on farmer-led targeting introduces a new comparative dimension to such data-driven discussions, which have relied mainly on content-based targeting [21].

Our contribution is to compare the efficiency of basic data-based targeting to the ability of farmers to predict information consumption on their own. As such, our results build on existing discussions on the demand for mobile innovations and the appeal of peer-recorded audio content in Indian agriculture [22-26]. However, we depart from that line of research in assessing the ability of farmers to use their own intuition to predict the other farmers that are more likely to engage with new content, compared to basic data-driven targeting using socioeconomic and agronomic indicators.

## 2 INFORMATION TECHNOLOGY FOR AGRICULTURE IN GUJARAT, INDIA

### 2.1 Geographic Context

Our study site is Gujarat, a state famously known as the "Jewel of Western India." Gujarat's capital city is Gandhinagar, while its largest city is Ahmedabad. Many rural and small-scale farmers grow cotton, castor and groundnut for subsistence and sell the surplus in the market. Farmers usually start making relevant decisions to maximize their yields on the beginning of planting season (June/July and November/December every year).

The government of India has funded large-scale agricultural extension programs to spread educational information about agricultural practices and technologies that can improve productivity, like the proper use of improved seeds, adequate fertilizer applications, as well as planting and harvesting techniques. The traditional model of agricultural extension consists of agents visiting farmers individually or in groups to demonstrate agricultural best practices. Unfortunately, only about 5.7 percent of farmers report receiving information about agricultural technologies from public extension agents in India [22]. Further complicating the matter is the fact that tastes and preferences for new information are dynamic and change with time and context. Since agriculture employs the broadest and most diverse demographic in India, collecting data about preferences and providing personalized educational services are often a costly endeavor for policy makers.

## 2.2 Khedut Saathi: Farmer's Friend

*2.2.1 Description.* Khedut Saathi (KS) is mobile voice service for small-scale farmers in Gujarat, India to receive and forward sustainable agriculture practice lessons in local languages over low-end phones. Khedut Saathi was created in and for this agricultural setting by our study partner, Awaaz.De Infosystems (Awaaz.De for short). The Khedut Saathi system builds on a prior mobile innovation also created by Awaaz.De: the popular interactive voice-based forum Avaaj Otalo (AO). Building a reputation and credibility among farmers in Gujarat for Awaaz.De, AO used interactive voice response (IVR) to transmit voice messaging to farmers as part of a mutually-active system, revealing a strong demand for peer-recorded content [23-26]. The AO system has significantly improved farmers' management practices [22]. Several IVR systems exist today that draw on this approach [12].

Farmers can subscribe to KS by leaving a missed call to a local phone number and pressing the number 9. Subscribers receive three voice messages each week about best agricultural practices for locally grown crops. When farmers receive a call from KS, an episode plays as an audio recording. After listening, farmers can record their questions and comments. KS leverages what farmers already have: low-end mobiles and personal social networks. To date, 12,000 farmers have subscribed to KS and only 1% have unsubscribed. The pickup rate of KS broadcasts is 75% on average, indicating a highly-engaged audience.

A unique feature of Khedut Saathi introduced for our study is forward-2-friend (F2F). Using F2F, our goal is to compare the farmers' ability to determine the recipients most likely to engage with content with the ability of targeting mechanisms based on demographic and agronomic indicators in the data. We measure farmer engagement by logging how long farmers listened to messages, and whether or not they listened to the complete message before hanging up.

The F2F feature provides novel opportunities for us to understand the robustness of allowing farmers to predict which of their own peers are most likely to desire to listen to different broadcasts. After hearing an episode, a farmer can enter up to 5 phone numbers to forward the episode to. To collect data with KS, we automatically record the phone numbers of farmers that engage with our content, how much time they spend listening to the messages, and how often they forward and receive messages.

In 6 months, KS episodes have been forwarded 2500 times by 1200 unique farmers to their social networks. We seek to understand how peer learning may occur in this context and how educational information diffuses among farmers for scale-up. Farmers are aware that messages originate from Khedut Saathi, but are unaware of whether and which farmers forwarded messages to them. In resource-constrained environments where censuses and household surveys are costly and mobile platforms are under-analyzed, we consider this research approach to constitute an option for gathering localized and timely information on social influence to understand the scale up of new educational information.

## 2.3 Data Collection Process

Study participants in Gujarat, India were randomly recruited from an Awaaz.De database to participate in a baseline survey, during which farmers self-reported sociodemographic and agronomic information. Baseline farmers were then selected for the study by stratifying on relevant sociodemographic and agronomic indicators.

To quantify how receivers of forwarded educational messages consume new information, our study proceeded in three general phases:

1. Collecting baseline information for a sociodemographic survey
2. Implementing the educational messaging and
3. Recording the forwarding and receiving information.

In the first phase, Awaaz.De collected a sociodemographic survey of farmers, asking the farmers to provide data on their age, gender, crop grown, educational attainment, income and whether or not they owned a smartphone. This baseline survey provides background information of the farmers. In the second phase, Awaaz.De creates new voice messages and disseminates this content as audio files to randomly-selected farmer phone numbers from the database of farmer numbers.

We sent four distinct voice messages in this manner, and each implementation was randomized. For simplicity, we will call this messaging implementation the treatment broadcast. Awaaz.De subsidized the airtime for farmers. The messaging was implemented in four rounds. The first message on fertilizer lasted for 125 seconds, the second message on pests and diseases lasted for 180 seconds, the message on seeds and planting lasted for 120 seconds and the fourth on fertilizer and pesticide lasted for 120 seconds.

We observe all calls to the service. After listening, farmers may choose to forward messages to other farmers as they wish. The receiving farmers have no way of telling who forwarded the message to them. Forwarder and receiver data were collected a day after the expert broadcast in each of the four rounds. This included data on how long farmers listened to the broadcasted content, and whether or not the farmers forwarded messages to other farmers.

Farmers sometimes forwarded messages to farmers who were not in our original baseline survey. When forwarded messages to new peers whose information was *not* available to Awaaz.De, the Awaaz.De data collector reached out to these new farmers and, with permission, performed a sociodemographic survey identical to the baseline survey performed on all farmers in the database.

## 2.4 Definitions

Our data is at the level of the phone numbers of farmers that participated in the study, with some farmers being messaged directly by Awaaz.De during the research, and others receiving messages from other farmers. The $data$ farmers refer to numbers generated based on agronomic and demographic indicators. $Forwarder$ farmers forward these messages to other farmers. $Receiver$ farmers are recipients of forwarded messages. The $forwarder$ farmers are connected to $receiver$ farmers in one-way transmissions, whereby a message can be forwarded to 5 receiver farmers at most.
The farmers are sampled and messaged in four consecutive rounds that coincided with the following different topics. Round 1 farmers are defined as those who were exposed to messaging on fertilizer; Round 2 messaging covered Pests and Diseases; Round 3 messaging focused on Seeds and Planting and Round 4 messaging was about Fertilizer and Pesticide.

## 2.4 Hypotheses

We anticipate that peer-to-peer mobile forwarding of resonant messages successfully predict which farmers are likely to be interested in specific content, relative to data-based targeting. We expect farmers to have a relatively strong intuition about what content would appeal to different kinds of farmers, based on their knowledge of those farmers, what they grow and their interests. If the appeal of a message exceeds an arbitrary threshold in terms of importance, it is likely forwarded by other farmers, and we expect farmers to play a decisive role in knowledge targeting.

## 2.5 Estimation Framework

We estimate Ordinary Least Squares regressions of the form

$$y_i = \beta_0 + \beta_1 T_{1i}^{RECEIVER} + X'_i\theta + \gamma Round_i + e_i \quad (1)$$

where $y_i$ refers to the duration or how much time is spent listening to a message; $\beta_0$ is a constant term; $T_{1i}^{RECEIVER}$ is a dummy variable denoting whether or not the farmer $i$ picked up and listened to messages forwarded to this farmer $i$ by another farmer; $X'_i$ is a vector of control variables generated by the socioeconomic data (age, gender, crops grown (cotton, castor, groundnut), educational attainment, income (in Indian Rupees (INR): 1INR = \$0.015), and whether or not the farmer owns a smartphone. The variable $Round_i$ refers to dummy variables based on one of the four possible message topics.

To isolate the effect of data-driven messaging, we only slightly adjust our regression specification:

$$y_i = \beta_0 + \beta_1 T_{1i}^{DATA} + X'_i\theta + \gamma Round_i + e_i \quad (2)$$

so that $T_{1i}^{DATA}$ refers to treatment farmers whose numbers were generate based on the following sociodemographic or agronomic indicators: income levels, educational attainment and crops grown.

# 3 RESULTS AND DISCUSSION

## 3.1 Summary Statistics

Table 1 shows descriptive statistics of the data. The table shows averages for the socioeconomic baseline variables (age, gender (male), crop grown, educational attainment, incomes and smart phone ownership). The farmers who participated in the study average 29 years of age and are predominantly male, with about 95% of the sample being men. Means are provided with standard deviations also reported. Our data consists of farmers who grow three commonly-grown crops in Gujarat: cotton, castor, and groundnut, with cotton being the most prevalent with 43% of farmers growing it. In terms of educational attainment, most of the farmers had experienced some post-primary education (nearly 60% of the sample). We also report smart phone ownership (gained by identifying farmers who report being able to use the application WhatsApp on their phone) and incomes. The farmers' annual income averages 213,028 INR, which breaks down to about \$8 per day. As a reference, the 2011 poverty line in India was at \$3 per day, implying that the farmers are above the poverty line, but are still largely smallholders. We also report data on the farmers' social media use in Panel A of Table 1. After the messaging was implemented by Awaaz.De, farmers were allowed to forward messages to up to five other farmers of their choice. The amount of time spent listening to messages was recorded for all farmers; whether they forwarded messages, whether they received forwarded messages, or whether they simply listened to Awaaz.De messaging but declined to forward About 94% of the farmers in the data were sent messages from Awaaz.De. About 4% of the farmers forwarded messages, and 6% of the farmers received forwarded messages from other farmers. The farmers whose numbers were generated from the original random sample listened for an average of about 50 seconds. Forwarders of Awaaz.De messaging spent 118 seconds and receivers of forwarded messages from peer farmers spending 86 seconds listening to messages on average. We also collect averages on effective duration: the proportion of farmers who listened to an entire message broadcast. Nearly half of the farmers listened to an entire message at least once.

**Table 1: Baseline Demographic Characteristics and Social Media Use**

| Variables | (1) Mean | (2) Standard Deviation |
|---|---|---|
| *Panel A: Demographics* | | |
| Age of farmer (Years) | 29.23 | 16.84 |
| Gender (Male) | 0.95 | 0.21 |
| Crop: Cotton | 0.43 | 0.49 |
| Crop: Castor | 0.24 | 0.43 |
| Crop: Groundnut | 0.32 | 0.46 |
| Education (None) | 0.12 | 0.32 |
| Education (Primary) | 0.29 | 0.45 |
| Education (Secondary) | 0.60 | 0.49 |
| Income (INR) | 213028 | 1699983 |
| Own a Smart phone | 0.39 | 0.49 |
| *Social media variables* | | |
| Duration (seconds) | 51.73 | 69.52 |
| Effective Duration | 0.38 | 0.51 |
| Listen to whole message | 0.29 | 0.45 |
| Data | 0.94 | 0.24 |
| High-income-targeting | 0.11 | 0.31 |
| Primary education-targeting | 0.28 | 0.45 |
| Secondary education-targeting | 0.58 | 0.49 |
| Cotton-specific messaging for cotton farmers | 0.12 | 0.32 |
| Forwarder | 0.04 | 0.20 |
| Receiver | 0.06 | 0.24 |
| New number | 0.10 | 0.30 |
| Round 1 messaging (Topic: Fertilizer) | 0.23 | 0.42 |
| Round 2 messaging (Topic: Pests and Diseases) | 0.11 | 0.31 |
| Round 3 messaging (Topic: Seeds and Planting) | 0.13 | 0.33 |
| Round 4 messaging (Topic: Fertilizer and Pesticide) | 0.54 | 0.50 |
| Duration for data | 49.83 | 68.61 |
| Duration for forwarders | 118.40 | 127.55 |
| Duration for receivers | 86.43 | 75.85 |
| Effective duration for data | 0.37 | 0.50 |
| Effective duration for forwarders | 0.89 | 0.99 |
| Effective duration for receivers | 0.61 | 0.54 |
| Observations | 1900 | |

In Panel B, we further break down the messaging round characteristics based on the content of messages provided in each round. During each round, we receive new numbers that were not part of the original baseline survey, and we follow up with such farmers and add them to the study.

*Panel B: Messaging Round Characteristics*

| |
|---|
| **Round 1 Content:** *How much fertilizer to apply, and things that need to be care of while applying fertilizer (125 mins.)*<br>256 treatment farmers messaged<br>59 forwarders<br>117 new numbers added to baseline survey |
| **Round 2 Content:** *Pests and diseases – Treatment for pink bollworm and sucking pests (180 mins.)*<br>128 treatment farmers messaged<br>5 forwarders<br>28 new numbers added to baseline survey |
| **Round 3 Content:** *When to plant and what seeds to use (180 mins.)*<br>178 treatment farmers messages<br>13 forwarders<br>30 new numbers added to baseline survey |
| **Round 4 Content:** *Fertilizer and Pesticide (120 mins.)*<br>713 treatment messages<br>11 forwarders<br>35 new numbers added to baseline survey |

## 3.1 Regression Analyses

*3.1.1. Main Regression Results from Peer Targeted Messages.* We now look at the effects of farmer-initiated message forwarding to quantify how effective peers are at identifying and targeting farmers whose would be interested in messages. In Table 2, we use OLS regressions to investigate whether farmers' intuitions significantly affect time spent listening to messages (measured in the duration or time spent listening to forwarded messages). All regressions control for all of the socioeconomic baseline variables (age, gender (male), crop grown, educational attainment, incomes and smart phone ownership). Farmers who do not listen at all are coded as zero, in part due to the small sample size. The receiver farmers predicted by peers spend a significant amount of time listening to messages received from fellow farmers. We find that peer-identified farmers (who receive messaging from other farmers) listen to about 54 seconds more in the simplified regression, which excludes the message topic round dummies. These are the "receiver farmers" of Table 2. When the message dummies are included in the regressions, we find that receiver farmers listen to about 45 seconds more. The magnitudes imply a strong influence for receiving messages from fellow farmers. The sociodemographic variables are not found to be significant, and the regression result is robust to including the message topic rounds.

*3.1.2. Ruling Out Novelty Effects.* It is possible that the effects we are seeing are partly explained by novelty effects: messages being forwarded to entirely new phone numbers that are not in our baseline survey, and hence unlikely to be exposed to Khedut Saathi, or its predecessor, Avaaj Otalo. In Table 3, we account for potential novelty effects by running the same regression while controlling for numbers that were not in the original baseline. Since results in Table 2 are robust to the inclusion of new numbers, we rule out the possibility of reaching entirely new farmers, as we find peer effects to still be statistically significant.

**Table 2: Effects of Farmer-Driven Messaging on Duration**

| Variables | (1) Duration | (2) Duration |
|---|---|---|
| Receiver | 54.28*** | 44.89*** |
| | (13.05) | (13.03) |
| Age | 0.0491 | 0.0286 |
| | (0.0970) | (0.0965) |
| Male | -0.180 | -7.770 |
| | (6.330) | (6.306) |
| Cotton | -4.586 | -3.633 |
| | (20.43) | (20.23) |
| Castor | -17.60 | -13.31 |
| | (20.09) | (19.85) |
| Groundnut | -13.43 | -12.41 |
| | (20.46) | (20.22) |
| Education | 11.32** | 4.693 |
| (Primary) | (5.480) | (5.391) |
| Education | 3.625 | -3.357 |
| (Secondary) | (4.731) | (4.680) |
| Income | 4.16e-07 | 9.02e-07 |
| | (7.49e-07) | (7.55e-07) |
| Smart phone | -7.395** | -6.533** |
| | (3.244) | (3.199) |
| Round 1 | | 21.10*** |
| Dummy | | (4.369) |
| Round 2 | | 21.38*** |
| Dummy | | (6.036) |
| Round 3 | | 29.40*** |
| Dummy | | (5.891) |
| Constant | 56.41*** | 58.20*** |
| | (21.63) | (21.46) |
| Observations | 1,900 | 1,900 |
| R-squared | 0.029 | 0.056 |

Robust standard errors in parentheses. *p<0.1; ** p<0.05 ***p<0.01%.

**Table 3: Effects of Farmer-Driven Messaging on Duration, controlling for new numbers**

| Variables | (1) Duration | (2) Duration |
|---|---|---|
| Receiver | 48.60*** | 38.32** |
| | (15.64) | (15.49) |
| New number | 9.187 | 10.59 |
| | (10.54) | (10.22) |
| Age | 0.0452 | 0.0241 |
| | (0.0971) | (0.0966) |
| Male | -0.363 | -7.999 |
| | (6.338) | (6.317) |
| Cotton | -1.129 | 0.361 |
| | (19.92) | (19.72) |
| Castor | -14.82 | -10.09 |
| | (19.55) | (19.31) |
| Groundnut | -9.949 | -8.388 |
| | (19.95) | (19.71) |
| Education | 11.36** | 4.729 |
| (Primary) | (5.480) | (5.391) |
| Education | 3.596 | -3.405 |
| (Secondary) | (4.727) | (4.679) |
| Income | 4.08e-07 | 8.94e-07 |
| | (7.49e-07) | (7.54e-07) |
| Smart phone | -7.406** | -6.545** |
| | (3.244) | (3.199) |
| Round 1 | | 21.16*** |
| Dummy | | (4.369) |
| Round 2 | | 21.45*** |
| Dummy | | (6.039) |
| Round 3 | | 29.44*** |
| Dummy | | (5.891) |
| Constant | 53.24** | 54.55*** |
| | (21.18) | (20.99) |
| Observations | 1,900 | 1,900 |

| | | |
|---|---|---|
| R-squared | 0.030 | 0.056 |

Robust standard errors in parentheses. *p<0.1; ** p<0.05 ***p<0.01.

*3.1.3 Regression Results from Peer Targeted Messages, focusing on whether farmers listened to the full message.*

We also assess whether being a receiver of forwarded messages makes a farmer more or less likely to listen to an entire broadcast. The fertilizer message broadcast lasts for 125 seconds; the message on protecting crops from pests and diseases lasts for 180 seconds; the broadcast on planting seeds lasts for 180 seconds and the message on pesticides and fertilizer lasts for 120 seconds. Farmers who listen to at least these cut-off points are therefore safely assumed to have listened to the entire message in each case.

In Table 4, we present evidence that farmers who receive forwarded messages from peers are more likely to listen to the full broadcast. This allows us to isolate farmers we can reasonably expect to have full benefit from the broadcasts, and whether farmer-based targeting plays a dominant role in selecting such farmers. The results are based on a probit regression, analyzed in an identical manner to the OLS regressions.

**Table 4: Effects of Farmer-Driven Messaging on Listening to an entire message**

| Variables | (1) Listened to entire message |
|---|---|
| Receiver | 0.526*** |
| | (0.198) |
| Age | 0.000942 |
| | (0.00184) |
| Male | 0.182 |
| | (0.153) |
| Cotton | -1.153*** |
| | (0.266) |
| Castor | -1.056*** |
| | (0.266) |
| Groundnut | -1.257*** |
| | (0.268) |
| Education (Primary) | 0.226** |
| | (0.105) |
| Education (Secondary) | -0.0688 |
| | (0.0991) |
| Income | 1.56e-09 |
| | (1.79e-08) |
| Smart phone | -0.0399 |
| | (0.0639) |
| Constant | 0.302 |
| | (0.317) |
| Observations | 1,987 |

Robust standard errors in parentheses. *p<0.1; **p<0.05 ***p<0.01.

*3.1.4 Main Regression Results from income Data-driven Targeting.* We now look at the efficiency of using agronomic and demographic indicators to target farmers that are most likely to listen to educational content. If the agronomic and sociodemographic factors are relatively important, farmers identified in this way should spend significantly more time listening to educational content. We assess whether targeting based on the agronomic and demographic indicators has a stronger effect than the farmer-based targeting noted above. In Table 5, we quantify the effect of data-driven targeting focusing on high income farmers: farmers with above-average income. We find that data-led targeting by income does not have a statistically significant effect on duration. We also find that targeting farmers based on their earnings does not have a statistically significant effect on whether farmers listen to the entire broadcast.

**Table 5: Effects of Income-led Messaging on Duration**

| Variables | (1) Duration | (2) Listened to the entire message |
|---|---|---|
| High income-targeting | -2.747 | -0.0502 |
| | (4.688) | (0.107) |
| Age | 0.0358 | 0.00143 |
| | (0.0963) | (0.00187) |
| Male | -7.414 | 0.0587 |
| | (6.282) | (0.156) |
| Cotton | -46.55*** | -1.195*** |
| | (16.07) | (0.246) |
| Castor | -54.16*** | -1.097*** |
| | (16.10) | (0.248) |
| Groundnut | -55.71*** | -1.304*** |
| | (16.00) | (0.247) |
| Education (Primary) | 3.361 | 0.112 |
| | (5.378) | (0.107) |
| Education (Secondary) | -4.012 | -0.149 |
| | (4.680) | (0.102) |
| Income | 1.08e-06 | 1.15e-08 |
| | (8.10e-07) | (1.81e-08) |
| Smart phone | -6.815** | -0.0659 |
| | (3.209) | (0.0645) |
| Round 1 Dummy | 23.41*** | 0.577*** |
| | (4.323) | (0.0770) |
| Round 2 Dummy | 21.88*** | 0.113 |
| | (6.106) | (0.107) |
| Round 3 | 29.48*** | 0.247** |

| | | |
|---|---|---|
| Dummy | (5.897) | (0.101) |
| Constant | 101.6*** | 0.376 |
| | (17.53) | (0.301) |
| Observations | 1,900 | 1,987 |
| R-squared | 0.050 | |

Robust standard errors in parentheses. *p<0.1; **p<0.05 ***p<0.01.

*3.1.5 Regression Results from Data-Driven Targeted Messages, targeted by farmer educational levels*

We also evaluate whether targeting farmers based on their educational attainment affects duration and whether or not such farmers are more likely to listen to an entire broadcast. According to Table 6, targeted farmers who had some primary education were significantly less likely to listen to content, and less likely to listen to an entire broadcast.

**Table 6: Effects of Primary Education-Data-Driven Targeting**

| Variables | (1) Duration | (2) Listened to the entire message |
|---|---|---|
| Primary Education-targeting | -93.54*** | -5.140*** |
| | (15.40) | (0.165) |
| Age | 0.0301 | 0.00131 |
| | (0.0963) | (0.00187) |
| Male | -7.292 | 0.0608 |
| | (6.275) | (0.155) |
| Cotton | -32.69** | -1.103*** |
| | (15.56) | (0.256) |
| Castor | -40.42*** | -1.007*** |
| | (15.59) | (0.258) |
| Groundnut | -41.55*** | -1.206*** |
| | (15.54) | (0.257) |
| Education (Primary) | 95.39*** | 5.230*** |
| | (15.54) | (0.182) |
| Education (Secondary) | -4.300 | -0.153 |
| | (4.658) | (0.101) |
| Income | 9.46e-07 | 9.13e-09 |
| | (7.56e-07) | (1.75e-08) |
| Smart phone | -6.639** | -0.0600 |
| | (3.212) | (0.0645) |
| Round 1 Dummy | 23.23*** | 0.576*** |
| | (4.313) | (0.0769) |
| Round 2 Dummy | 20.82*** | 0.0803 |
| | (6.041) | (0.109) |
| Round 3 Dummy | 29.86*** | 0.254** |
| | (5.882) | (0.100) |
| Constant | 87.86*** | 0.284 |
| | (17.03) | (0.307) |
| Observations | 1,900 | 1,987 |
| R-squared | 0.056 | |

Robust standard errors in parentheses. *p<0.1; ** p<0.05 ***p<0.01.

*3.1.6 Main Regression Results from Data-driven Targeted Messages focusing on Crop-Specific Messaging.*

We now focus on crop-specific messaging related to cotton and sent to cotton farmers. The sample in this sub-section consists of all farmers used in the study, to be as representative as possible in our results. We focus on farmers of cotton who were exposed to cotton-based messaging as our treatment variable to understand the effects on duration and the likelihood of listening to an entire message. In Table 7, we find that farmers who received their messaging in this module show a positive effect on duration, although the effect is not significant. We find that farmers who were targeted using the cotton-specific messaging approach were significantly less likely to listen to the entire message with the full regression. It appears to be the case that cotton farmers also have crop-specific needs that influence their listening outcomes so that they generally stop listening as soon as their needs have been addressed.

**Table 7: Effects of Cotton-data-based Messaging on Duration and Listening to the Entire Message**

| Variables | (1) Duration | (2) Listened to the entire message |
|---|---|---|
| Cotton messaging targeting cotton farmers | 5.449 | -0.414*** |
| | (7.577) | (0.126) |
| Age | 0.0467 | 0.00171 |
| | (0.0962) | (0.00185) |
| Male | -7.202 | 0.0440 |
| | (6.316) | (0.155) |
| Castor | -7.099* | -0.0861 |
| | (4.205) | (0.0863) |
| Groundnut | -8.524** | -0.286*** |
| | (3.898) | (0.0841) |
| Education (Primary) | 2.229 | 0.104 |
| | (5.379) | (0.105) |
| Education (Secondary) | -4.757 | -0.160 |
| | (4.698) | (0.0997) |
| Income | 9.39e-07 | 1.04e-08 |
| | (7.57e-07) | (1.76e-08) |
| Smart phone | -7.244** | -0.0935 |
| | (3.211) | (0.0646) |
| Round 1 Dummy | 22.58*** | 0.805*** |
| | (4.970) | (0.0894) |
| Round 2 Dummy | 21.72*** | 0.335*** |
| | (6.461) | (0.114) |
| Round 3 Dummy | 29.86*** | 0.236** |
| | (5.883) | (0.101) |

| | | |
|---|---|---|
| Constant | 54.74*** | -0.702*** |
| | (7.964) | (0.179) |
| Observations | 1,900 | 1,987 |
| R-squared | 0.046 | |

Robust standard errors in parentheses. *0.1; **0.05 ***p<0.01.

*3.1.7. New Calls to the Khedut Saathi Service*

To understand whether offline peer recruitment complements the online peer targeting we have documented, we also look at offline interest and recruitment using Khedut Saathi records during the study. We examine repeated inbound calls to the Khedut Saathi system by farmers who were neither in our database nor regular users of the service nor recipients of forwarded messages. We find a strong growth in new usage, which we attribute to offline interest and discussions among users of the service with fellow farmers who are not Khedut Saathi users. Farmers note that they often socialize with other farmers offline, and this context probably played a role in further scaling the Khedut Saathi service. A minority of these new numbers might reflect the use of new Subscriber Identity Module (SIM) cards by existing Khedut Saathi users, although the very large volumes observed imply that such farmers are likely to be a very small minority.

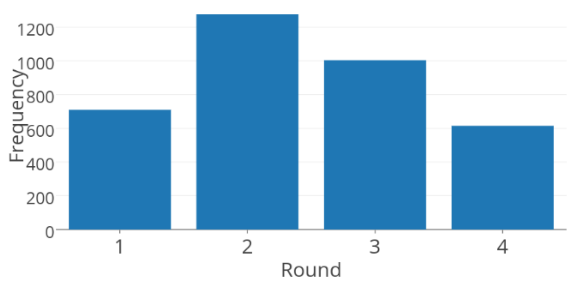


**Figure 1: New inbound calls to Khedut Saathi over time**

Fig. 1 documents repeated in-bound calls of entirely new numbers, grouped by the specific message topic round which was in session while the new numbers attempted to reach the Khedut Saathi system. New users listen for about 78 seconds on average, compared to the baseline average of about 50 seconds. The strong interest from unique new numbers, coupled with the strong utility farmers attach to new information from our interviews, imply that Khedut Saathi has strong importance for farmers both offline and online.

## 4 DISCUSSION OF RESULTS

Summarizing the regression tables, our overall finding is that farmer-led targeting performs significantly better than these simple data-based approaches, leveraging farmers' intuition about which other farmers in their social networks are more likely to listen to a broadcast. Farmers are also better at knowing who would listen to a full message broadcast before hanging up than the data-based approach. Tracking the growth in new inbound calls to the information service is one way to help further gauge interest in educational content. Although more complex methods might improve targeting outcomes, such approaches would likely require more high-dimensional data.

### 4.1 Farmer Impressions of Khedut Saathi

To contextualize our quantitative results, we also performed open-ended interviews with farmers to understand their forwarding and receiving behavior. When asked why they chose to forward messages, one farmer said "if a message is useful, I want my friends to listen to it so they can apply it in the field and get similar benefits". Such responses imply that farmers have an intuitive awareness of the needs of their peers and forward messages that they themselves find valuable.

We also uncover reasons why some farmers may not forward messages. Some farmers felt assured that their colleagues and friends would get access to the messages on their own: "my friends also get these messages so I don't forward." Farmers who did not forward messages were occasionally illiterate: "I am illiterate, I don't know how to forward," as one farmer stated. About 90% of forwarder farmers had access to at least primary education in the data. Some of the farmers who didn't forward felt that the process of forwarding a message was not always easy, perhaps since one needs to enter a ten-digit mobile number. Although receiver farmers did not know the source of messages, they seemed to have strong preferences for new information overall. As one farmer put it "Information is good. So I listen. I don't know whoever sends it." This acknowledged importance of messaging is understood within the context of needs such as protecting farm crops from pests such as the pink bollworm, a topic covered in the second round of our data collection. In Gujarat, pink bollworms affect cotton farming by disrupting protective crop tissues and enables other pests to diminish crop quality. This outcome provides some of the context for farmers' appreciation of relevant messaging.

The farmers also had feedback for the Khedut Saathi providers that have broader policy implications. The farmers appeared to particularly approve of the quality of information, based on their experiences and observed results. "Information quality is good." as one farmer put it. Another felt that the content was "Good information, right information. Something which is useful for farmers." We also found that some farmers preferred to tell friends about messages in person instead of forwarding messages by phone: "I tell them when I meet." This outcome confirms our finding that offline peer interactions are also important.

## 5 CONCLUSIONS

In summary, peer-led targeting may be more efficient than simple data-based targeting used to scale up new information for precision agriculture. Agricultural advisory services often waste valuable resources in delivering messages to indifferent farmers, perhaps at the expense of interested audiences that are under-targeted or ignored. Even if farmers only listen to short sections of these messages, organizations (and/or users) incur airtime costs for as long as they listen. Such organizations also waste scarce resources in collecting data about such farmers as well. Harnessing the intuitions and predictions of farmers is one way to improve the efficiently of targeting. Related settings with informational and social relationship contexts, such as community health worker training or education initiatives may similarly benefit from our approach.

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