Training through A Mobile App: Evidence from A Randomized Controlled Trial in China

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Abstract

The application of information and communication technologies could be a viable alternative to traditional agricultural extension services in developing countries. We develop a mobile application-based training module intended to improve the quality of grapes and use a randomized controlled trial to examine its effectiveness. We find that providing technical training through a mobile app can improve farmers' knowledge and helps them enhance the quality of their produce. We also find that motivating farmers through the mobile app is not effective and undermine the impact of increased knowledge. Bundling motivation with technical training can lead farmers to overestimate the quality of their products. It suggests that training through mobile apps that focuses on the technical module is more desirable.

Keywords: Technology adoption, ICT in agriculture, training, product quality.

JEL Codes: O13, Q16, L86.

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1 Introduction

Farmers in developing countries usually lack access to vital resources and services that facilitate the adoption of new technology and improved farming practices. Lack of information—particularly technical know-how—and knowledge are widely accepted to be critical barriers to adopting new technology (Foster and Rosenzweig, 1995, 2010; Magruder, 2018). Agricultural extension services, including technical training, are an important method to overcome these deficiencies and reduce poverty by providing information and transferring knowledge to farmers (Anderson and Feder, 2004; Nakasone, Torero and Minten, 2014). In the absence of a proper agriculture extension service, information transfer can be scant or ineffective (Takahashi, Muraoka and Otsuka, 2020). Extension services that facilitate farmers' technical training and transfer of information can improve technology adoption and farmer productivity (Bellemare, 2010; Davis, Nkonya, Kato, Mekonnen, Odendo, Miiro and Nkuba, 2012; Godtland, Sadoulet, Janvry, Murgai and Ortiz, 2004; Grimm and Luck, 2020; Magnan, Hoffmann, Opoku, Gajate Garrido and Kanyam, 2021; Pan, Smith and Sulaiman, 2018). Traditional extension service typically entails a great number of human resources as well as high fixed and recurrent financial costs (Quizon, Feder and Murgai, 2001) that limit their scalability and efficiency. For instance, traditional extension services in the form of in-person training often involve low-frequency visits that occur outside the planting and harvest seasons due to constraints brought about by distance and time (Cole and Fernando, 2021).

While these factors limit farmers' access to timely and high-quality agricultural information and extension services (Ferroni and Zhou, 2012), the rapid expansion of information and communication technologies (ICTs) in developing countries offers great potential to overcome the myriad challenges presented by knowledge delivery in the rural setting (Aker, 2011; Fabregas, Kremer and Schilbach, 2019). Though ICTs include different types of technologies such as radio, television, computer, and mobile phones, mobile phones are the most widely accessible, and owing to its rapid penetration, it has the biggest potential to increase agricultural productivity.[1] For instance, voice and SMS messaging have been shown to be effective in delivering vital information to farmers (Cole and Fernando, 2021; Fu and Akter, 2016; Larochelle, Alwang, Travis, Barrera and Dominguez Andrade, 2019). See (Aker, Ghosh and Burrell, 2016) for a detailed discussion). While ICT has substantial promise in agriculture, its adoption needs to consider the provision of accurate information, digital literacy, and proper monitoring of actual usage by its intended beneficiaries (Lele and Goswami, 2017).

This paper uses a two-arm cluster-randomized controlled trial (RCT) to study the impact of providing technical training through an easy-to-use mobile application on farmers' technical knowledge and adoption of technology. Our analysis is based on a sample of grape farmers in rural China. We develop a mobile app that contains and disseminates technical training videos for each stage of the grape farming cycle. In addition, we provided aspirational videos via the same app, which demonstrated success stories of farmers who had adopted the techniques being taught through the app. Access to the technical as well as the aspirational videos was randomized on a sample of 1,026 farmers. The first treatment arm received technical videos only, while the second treatment arm received both technical and aspirational videos. The control group farmers received placebo videos depicting the landscape of the region; these videos were accessible to the treatment groups as well. We helped farmers install the app on their phones before the farming season and uploaded timely and relevant content throughout the grape planting season in 2020.

We find that providing training through pre-recorded videos sent to a mobile app is an effective alternative to traditional extension services for improving farmers' knowledge. Our results show that farmers did spend time watching the videos watch videos, commonly during their breaks on workdays, thereby allowing farmers to learn new techniques without taking time off during their working hours or weekends. Our findings suggest that providing cash incentives to watch videos may improve farmer uptake.

We show that mobile app-based training can work as a substitute for in-person training.

[1]Around 83 percent of adults in developing counties had a mobile phone in 2018 (Klapper, 2019).

Traditional agricultural extension requires high fixed costs and large person-time commitment (Kondylis, Mueller and Zhu, 2017; Maertens, Michelson and Nourani, 2021). We find evidence that farmers in both our treatment arms have improved technical know-how due to our intervention. Farmers in both treatment groups experienced an increase in their knowledge by 0.45 to 0.52 standard deviations (SDs) over the control group (a 9.4 to 10.8 percent increase in raw means).

We find that providing focused training to farmers helps them achieve a higher quality product. Given farmers who receive the training may misreport their adoption status (Fabregas et al., 2019), we rely on an objective measure of quality (sweetness) that would be directly affected by the knowledge disseminated in the training. Farmers in our training-only arm improve the sweetness of their product by 0.297 SDs. Farmers in the aspirational group do not experience any increase in the sweetness of their grapes. We also do not find any impact of the intervention on other measures of quality, i.e., the number of grapes in a bunch and the weight of a bunch. We also find that despite increasing farmers' knowledge, the intervention also leads farmers to overestimate the quality of their products.

We find weak evidence of any impact of the aspirational videos on farmers' aspiration. The aspirational arm farmers only exhibit an increased aspiration of producing sweeter grapes in three years (a two percent increase in raw control mean and statistically significant at 10 percent level). We do not find any impact of the intervention on farmers' aspired income in three years or aspired income and sweetness of grape in five years.

Our main results survive several robustness checks. First, we do multiple hypothesis testing by calculating ajdusted sharpened-q values using the methods suggested by Anderson (2008) based on Benjamini, Krieger and Yekutieli (2006). While the sharpened q-values are higher than the *p*-values for a majority of our main outcome variables, they are within the threshold of statistical significance. Second, we deviate from our preferred specification by choosing control variables implementing using the double LASSO method of Chernozhukov, Chetverikov, Demirer, Duflo, Hansen and Newey (2017). Our main results remain qualitatively similar when we include these control variables.

We argue that when a decentralized training modality is applied for farmers, bundling multiple learning objectives together does not yield the desired outcome. We find that while the training and aspiration arm increases the farmers' knowledge, it does not increase the sweetness of the grape. We find weak evidence of improvement of farmers' aspirations. Moreover, we find that farmers in these arms have a large overestimation of the quality of their products. This further suggests that digitally delivered training and in-person extension services may have a scale vs. intensity tension.

We do not find any significant impact of the intervention on other grape-related outcomes. While there is no significant impact of the training on grape production and revenue, the point estimates of the training-only arm for sale volume and revenue are in the desired direction. The weak effect of intervention on sales and revenue might be because the intervention farmers are relatively small in size to have any impact on the prices and revenue generated, suggesting that supply-side intervention may need coupling with demand-side intervention to achieve the desired outcome of improved farmer welfare.

This paper contributes to the literature on agricultural technology adoption through ICTs in developing countries (Fabregas et al., 2019; Nakasone et al., 2014). We also contribute to the growing literature on digital extension services (Arouna, Michler, Yergo and Saito, 2021; Oyinbo, Chamberlin, Abdoulaye and Maertens, 2021; Spielman, Lecoutere, Makhija and Campenhout, 2021). An appropriate mode of delivering information through mobile phones is important in making the information effective. Voice messages (Cole and Fernando, 2021; Walter, Kremer, Reich, Sun, van Herwaarden and Yesigat, 2021) and SMS messages (Casaburi, Kremer, Mullainathan and Ramrattan, 2019; Fafchamps and Minten, 2012; Larochelle et al., 2019) are the popular methods that have been studied in the literature. However, certain kinds of information may be too complicated to convey by text or voice (Fabregas et al., 2019), our mobile app addresses this issue by effectively communicating through pre-recorded videos. Additionally, the background tracking of app usage gives us a correct measure of the use of technology.

To the best of our knowledge, this is the first paper that uses a mobile app-based video-delivery of farmer training. Fu and Akter (2016) studied audio-visual communication in solving farmers' problem, while Hörner, Bouguen, Frölich and Wollni (2022) screened movies that discussed the adoption of the said technology to help farmers. Our study focuses on providing training (hence, not demand driven) at the doorstep of the farmers on their mobile phones so that they can look at any time they want. While the use of mobile apps has been studied in the context of agricultural extension as well (Van Campenhout, 2017), that study does not focus on extensive app-based training using videos. In addition, it is usually difficult to observe whether farmers read the text and document which content the farmer asked via voice calls. Since our mobile app automatically records app usage, we are able to identify what, when, and how long the farmer watched each video in our app. This notable feature may help extension agents or researchers better understand farmers' needs and make adjustments accordingly. Furthermore, a mobile app allows us to provide interventions, such as offering aspiration videos, that can enhance farmers' psychological well-being (Ridley, Rao, Schilbach and Patel, 2020) and may facilitate learning among farmers (Fabregas et al., 2019).

The rest of the paper is organized as follows: we discuss the background and experimental design in the following section. In section 3, we discuss the data collection timeline and describe our data. We enumerate the empirical strategy in section 4, followed by a discussion of results in section 5. Section 6 concludes the paper.

2 Background and Experimental Design

2.1 Study Setting

This study takes place in Beizhen of the Liaoning province, one of the largest grape-producing regions in China. The economy of Beizhen is agriculture-oriented, and there are roughly 10,000 grape farming households. As Chinese consumers are demanding greater food quality (Huang and Gale, 2009), the market for low-quality grapes, mainly due to low sweetness, has been shrinking and the prices have been dropping in the past few years. However, most growers still prioritize yield over quality and have settled on a high-yield cultivation and management model despite the rise in demand for high-quality grapes. As a result, they fail to pay attention to the quality of the fruit, which leads to loose fruit clusters, large and small grains, poor fruit coloring, and insufficient sugar content.

Being aware of this market change, the local government of Beizhen has been trying different ways to help farmers improve their grape quality, such as offering in-person training sessions by experts. The necessity of training was corroborated by our baseline, where only 50 percent of the farmers could correctly mention the frequency and amount of watering during the fruit expansion period that affects the shape, weight, and sugar content of the bunches and improves the quality of the grapes.

Nevertheless, despite the local provision of training such as field demonstrations, most farmers are unable to learn new farming techniques. Many growers were able to understand the knowledge presented on-site, but did not know how to combine it with their own grape production: for example, the training experts would use a PowerPoint presentation to demonstrate the technical process of pruning fruit trees, but the growers still did not know how to cut the branches back in their own orchards. This kind of traditional on-site training may not effectively transfer information and fail to meet the needs of growers in the whole process of production. In addition, traditional training methods are generally expensive.

Thus the search for innovative ways to raise farmers' grape quality has become a pressing challenge for the local government.

With this goal in mind, we partnered with the Beizhen government to explore interventions that leverage modern ICT infrastructure that are increasingly viewed as a potential substitute for traditional information interventions. Given the near universal accessibility of mobile internet in China[2], we developed a mobile application that can provide technical training to local grape farmers. Figure B1 shows the interface of this mobile application. We then study whether the provision of technical training, in the form of short and accessible videos hosted on this custom mobile application could be viable alternative to traditional forms of agricultural extension service.

2.2 Content of the Videos

The mobile app released a series of videos aimed at boosting farmers' technical knowledge on farming practices that raise grape quality. Videos were released throughout the planting season between May and September. Grape production in Beizhen can be divided into 5 stages: budding and leafing period (May), flowering and fruiting period (June), fruit expansion period (July), fruit coloring period (August), and ripening and harvesting period (September). At the key points of each period, we provide the corresponding content required for each of the four types of technologies: water management, fertilizer management, pest and disease management, and fruit pruning techniques, with different technical contents required for each month.

The content automatically downloads to the user's phone upon accessing the app while connected to the internet. Our goal is to increase farmers' technical skills, which can help

[2]China has a 67 percent internet penetration and 99 percent of its netizens access the internet using a mobile phone (CNNIC, 2020). More than 98 percent of rural villages in China have internet coverage, and the cost of accessing the internet is low (See Speakman (2020)). Furthermore, China has the most mobile app downloads in the world, and Chinese internet users spend more than 30 percent of total usage time on video apps (See Zinan (2019)). Hence, the potential reach of our mobile app is large.

them increase their grape quality and eventually increase the price of their grapes. Since lack of motivation may be another reason for farmers not to adopt the new techniques, we also offer motivational videos in our app to farmers in one of the two treatment arms.

We released three types of videos. The first set of videos consists of 60 technical videos that are between one and three minutes in length. Our technical videos mainly focused on controlling grape yield and improving grape quality. Topics include methods in pruning and thinning, water and fertilizer management, and pest and disease control.[3] Each video was designed to be relevant to the farmers' particular needs at each stage of the grape-planting cycle. Technical videos were explained by local leading farmers and large growers.[4]

The second set of videos were 15 aspirational videos promoting the practice of growing high-quality grapes. These videos featured prominent speakers from the Beizhen Grape Association—a group of farmers charged with ensuring standards of high-quality grapes in the region as well as promoting the wider adoption of the Beizhen grape brand in markets across China. In these videos, speakers like the chairman and vice-chairman of the association spoke about their own experiences raising the quality of their grapes and selling them under the Beizhen brand. These videos explained the standards of high-quality grapes in Beizhen for the majority of growers, talked about the development of the high-quality grape market in the next three years, and shared their own success stories with the Beizhen grapes brand.

Apart from technical and aspiration videos, we released placebo videos featuring the local history of the grape industry as well as the natural landscapes of the region. These were released to all farmers at different points throughout the study period.

[3]See Appendix C for a detailed description of the content and how they relate to different stages of grape production.

[4]The large growers have significant influence in promoting planting methods and changing output patterns. Since they control a large amount of land, they have considerable control over the agriculture. Over the years, large farmers have started paying special attention to fruit quality, risk avoidance, and innovation. They will use local climatic conditions, farming habits, and land level as the basis for judgment, make targeted production material input combinations, explore changes in planting patterns, and apply modern means to production.

2.3 Experimental Design

Our sample consists of farmers residing in the grape-growing regions of Beizhen. The criteria for inclusion in the sampling frame include: (1) the household engaged in grape farming in 2019; (2) the household resided within the seven townships with the largest concentration of grape farming to limit survey costs.

Our experiment follows a cluster randomized design with two treatment arms and a control group. The unit of randomization is the sub-village (zu) of residence, which was chosen to minimize contamination across groups. In total, our sample contains 116 clusters from 38 villages with a median number of 7 households interviewed per zu.

All farmers in the study received the mobile application, but the content released varied across treatment and control groups. All farmers received the placebo videos. Thirty-nine clusters were assigned to additionally receive the technical videos (Treatment Arm 1, or T1; N = 325). Another 39 were assigned to additionally receive both the technical videos aspiration videos (Treatment Arm 2, or T2; N = 332). Thirty-eight control group clusters receive only placebo videos (Control Group, or C; N = 369).

We started releasing videos in May 2020—the sprouting and leafing period—and continued to do so until mid-September 2020—the beginning of the harvest season. Figure 1 summarizes the quantity and timing of these video releases. Every release was accompanied by an SMS message alerting farmers to the update. We sent SMS alerts of video updates to growers every day at noon or evening when they return home after a break from farming.

In addition to the videos released through the app, we also provided monetary incentives for farmers to watch the videos. Specifically, beginning the end of June we told farmers that we would provide 2 RMB (0.3 USD) per video watched. These were applied uniformly across all groups regardless of the type of video. We issued a red envelope of 2 yuan for each video watched via WeChat (red envelopes are more popular in China, and people consider it a symbol of good fortune) and we emphasized that they had to watch a full video on the day they uploaded it to get the reward, which was to avoid farmers opening the video just for the monetary reward but not watching it.

3 Data Description

3.1 Data Collection

Our fieldwork took place from January 2020 to January 2021. The baseline data was collected in early January 2020 after the previous year's harvest season. Importantly, we were able to do this in person as this preceded the outbreak of COVID-19 in China.

The sample frame of growers surveyed in this study is the census database of grape growers in Beizhen, Liaoning Province, which includes 9767 grape growers in 52 villages in 10 townships in the city with grape cultivation. We first randomly selected seven townships, then randomly selected 38 villages, and finally randomly selected 1840 respondents from the sample frame to conduct a one-on-one household survey. We interviewed 1,042 farmers living in 38 villages of Beizhen and collected information regarding their grape production, sales, self-assessments of their own grape quality, as well as household demographics. We also conducted a short test of technical knowledge on grape farming and inquired about their aspired income and grape quality three and five years into the future. After screening, we had 1,026 farmers from 38 villages that constitute our baseline sample.

We conducted two short midline follow-ups with the farmers via phone call. The first follow-up transpired in early May of 2020, in which we asked farmers whether they were impacted by the pandemic and whether they were still planting grapes in that season. We also ensured that the apps were installed by each farmer as we started releasing the videos in the same month. A second follow-up was conducted in late June, in which we informed the farmers about the monetary incentives associated with watching the videos.

A more detailed in person midline survey was then conducted during the harvest period in

October 2020. We inquired about their grape production for the year, including investments in inputs and farming practices adopted. To measure grape quality, we collected both self-assessments similar to those collected at baseline and a sample of the farmers' grapes which we use to obtain an objective measure of grape quality (our main outcome of interest).

Finally, in January 2021, we conducted an endline survey in which we inquire about the farmers' total grape sales for the year. We also collected information regarding their grape storage and feedback regarding the mobile application. Due to logistical constraints imposed by the COVID-19 pandemic, only the baseline and September midline were administered in-person while the endline was administered via phone call.

3.2 Tracking App Usage

We collected app login data to track farmer's usage patterns of the app. Since the app automatically records the login time, stay time, and exit time of each farmer, we can observe whether the farmer has accessed the app, the number of times they have logged into the app, and the total amount of time they have spent on the app. Additionally, we can also track the frequency of watching each video and the total time spent watching that video. We had dedicated technical staff responsible for the maintenance of the app database. This includes database security and integrity control; database performance supervision, analysis, and transformation; database object reorganization and historical data migration, etc. According to the changes in the application environment, we readjust the app model to improve and enhance the growers' experience of using the app.

3.3 Measures of Farming Knowledge, Grape Quality, and Aspiration

Since farmers are likely to misreport knowledge and adoption of technology (Kondylis, Mueller and Zhu, 2015), we relied on objective measures of these outcomes. In order to measure farmers' awareness and knowledge of farming practices that improve grape quality, at the endline we asked the farmers 10 questions on a range of topics, including grapevine inflorescence, water and fertilizer use, disease prevention techniques, and pest control. We calculated the number of correct answers to these questions to calculate a knowledge score and standardized it with respect to the control group.

To measure the quality of farmers' grapes, we rely on both objective and subjective measures. Grape quality in our context can be judged along several dimensions, including sweetness, the shape of a grape bunch, the roundness of the individual berries, and the color of the fruit. As the local grape market is segmented into low- and high-quality markets, grapes that are sold in the latter are typically sweeter, form a conically shaped bunch, and have berries that are spherical. Moreover, high-quality grapes are normally priced between 1.5 to 2 times higher than low-quality grapes.

Apart from using price, a useful proxy to capture the overall quality of the grape is its sweetness. Grape sweetness is measured on a scale of 8-24 with the highest quality grapes having a rating of 20 or higher. We obtain an objective sweetness rating of the farmers' grapes measuring the sweetness of their produce using a sweetness measuring machine (See Figure B2). We collected a sample from their harvest during the 2020 grape season and placed the grapes in the machine to obtain an objective measure of quality. Because this scale of rating of sweetness is widely known among the farmers, we ask them about their own rating of their harvest, which we use as a subjective assessment of quality. This self-report measure is asked at both the baseline and the September midline.

Finally, to measure the aspiration of farmers, we follow Bernard, Dercon, Orkin and

Taffesse (2014) and asked farmers what level of income from grape farming they would like to achieve within a 3-year and 5-year horizon. Similarly, we ask farmers what level of grape quality (sweetness) they would like to achieve within a three-year and five-year time frame.

3.4 Farmer Characteristics and Sample Balance

In Table 1, we report summary statistics and tests of the balance of the baseline sample farmers. Our sample is balanced along several demographic and economic dimensions such as gender, age, health status, household size, years of grape planting, grape planting area, and grape yield. Our sample is about 70 percent male and on average 47 years old. The average household size in our sample is 3.8. Roughly 62 percent of the farmers completed middle school or above. Only 42 percent of the farmers report to have a good health. About 32 percent of the farmers reported to have previous training experience. Our sample farmers are highly experience - on average they have been producing grapes for 21.5 years. An average farmer plants on about 1.8 acre of land. We apply the inverse hyperbolic sine (IHS) transformation of yield, revenue, and prices. The average IHS yield of our baseline farmers was 11, while the IHS revenue and prices were 9.7 and 1.3, respectively.

Key outcome variables such as technical knowledge test scores, self-rated sweetness, aspired income, and aspired sweetness are also balanced across groups. We standardize test score, measures of quality, and measures of aspired quality with respect to the mean and standard deviation of the control group values. We IHS transform 3- and 5-year aspired income—the average baseline IHS values of them are 11.7 and 10.7, respectively.

However, we do find that our technical videos only (T1) group has a greater proportion of farmers that have completed middle school or above, and higher revenue from grapes. To address potential imbalance along observables, we include these variables as controls in robustness checks and find that our main results are robust to the inclusion of these additional control variables.

3.5 Analytical Sample and Attrition

From an initial baseline sample of 1,026, our analytical sample consists of 687 grape farmers whom we were able to successfully interview in all rounds. Figure B3 provides a snapshot of the timeline of data collection as well as the number of farmers lost at each wave.

While we experience large attrition, there is no systematic difference of attrition between experimental arms. Table A1 in Appendix A shows attrition in midline and endline. We did not find about 22% of baseline farmers at midline and 31% of baseline farmers at endline. As this table shows, there is no significant variation of attrition across treatment arms. Figure B4 shows the location of the baseline sample and the attrited sample.

4 Empirical Strategy

Our preferred specification is as follows:

$$y_{iz} = \beta_0 + \beta_1 T1_z + \beta_2 T2_z + X_{iz}^{'}\delta + \varepsilon_{iz} \tag{1}$$

where y_{iz} is the outcome of interest measured at endline for farmer i in zu z. $T1_z$ is a binary indicator variable that takes the value of 1 if zu z was randomly assigned to training-only arm and $T2_z$ is a binary indicator variable that takes the value of 1 if zu z was randomly assigned to training and aspiration arm. X_{iz} includes baseline characteristics. In our preferred specification, we only include outcome variable measured at the baseline when available. As a robustness check, in an alternate specifications, we additionally control for variables chosen following the post-double selection methods suggested by Chernozhukov et al. (2017). We feed the algorithm the following variables: farmer's gender, training status, completing middle school or above, having a good health; age, total household income, years of experience, baseline planting area, inverse hyperbolic sine of baseline yield and baseline revenue from grape, baseline knowledge, baseline aspiration variables, baseline self-reported sweetness of grape, and first-order interaction between each variable. All standard errors are clustered at the zu level. Since we assigned the treatment status randomly, estimates of β_1 and β_2 from equation 1 gives us the impact of T1 and T2. Thus all reported estimates are intent-to-treat (ITT) effects.

5 Results

We present three primary analyses. First, we analyzed whether the farmers watched the videos. Second, we analyzed whether the intervention improved their technical knowledge. Third, we further analyzed whether the intervention improved the quality of the grapes. We also looked at two secondary outcomes: farmers' aspiration and other grape related outcomes.

5.1 Video Watching

The treatment farmers spent more time using the app than the control group farmers. To asses whether the farmers watched the videos, we used two measures. First, we analyzed the number of hours spent on the app. We calculated the total amount of time farmers spent in each type of video (placebo, technical, aspirational) and used these as the outcome variable. Table ?? reports the results.

We find that both T1 and T2 group farmers spent more significantly more time than the control group farmers in watching the placebo videos (3.8 and 4.7 hours more, respectively). Consistent with our expectation, we also find that both the treatment group farmers spent more time watching the technical videos (22.4 and 23.8 hours more, respectively) since the control group farmers did not have access to the technical videos.[5] Notably, there is

[5] One control group farmer could watch the technical and aspirational videos due to a bug in the app.

no significant difference between the two treatment groups in terms of watching placebo and technical videos. Similarly, T2 farmers spend significantly more time watching the aspirational videos, which is expected as these videos were not accessible to other farmers.

Next, we look into the share of videos watched by the treatment arm. Here, the outcome variable is the share of total technical and aspirational videos watched by farmers. Table 3 shows that on average training arm farmers watch technical videos 22.2 percentage points more, while training and aspiration arm farmers watch those videos 26.6 percentage points more. Meanwhile, on average, T2 farmers watched only 9.3 percent of the aspiration videos.

We further analyze the share of videos watched each month. We find that the share of videos watched increases after we introduce the incentive to watch videos. Figure B5 shows the stark rise in farmers' interaction with the app once the incentive is introduced. While there is no significant difference between the two treatment groups in terms of share of all the videos watched, T2 group farmers watch significantly more technical videos than T1 group farmers (at the 10 percent significance level).

It does not appear that farmers spend additional time on the app by cutting down working hours or weekends. Farmers were most active on the app during the middle of the week, i.e., Tuesday-Thursday (Figure 2). In terms of time of day, they were most active in the evening—when they were resting after work—and at noon—during lunch hours (Figure 3).

5.2 Farmers' Knowledge

While the share of videos watched was low, we find that providing training through the mobile application is effective in increasing farmers' knowledge. We constructed two outcome variables based on the endline test to measure the impact of the training on farmers' knowledge. At the endline, we conducted a test of 10 questions. We count the total number of questions that each farmer answered correctly. For the first measure, we use all 10 questions. These 10 questions included five questions that were asked in both baseline and endline, while the rest were new questions asked only at endline. The second measure looks at the five questions that were repeated from the baseline. Both the measures are standardized by subtracting the control group mean and dividing by the control group standard deviation.

Table 4 shows that training arm increases farmer's overall test score by 0.52 standard deviations (10.8 percent increase in raw means), while training and aspiration arm increases test score by 0.45 SD (9.4 percent increase in raw means). Though given the relatively large raw control mean, the increase in test score is not extremely large, there is a clear positive impact of the training in increasing farmer's knowledge.

We also find that there is a significant increase in test scores when we only consider the repeated five questions from the baseline test (column 2). The test scores increased by 0.37 SD for T1 group farmers and 0.41 SD for T2 group farmers. We interpret this as evidence that mobile applications may be an effective means of providing technical training, at least insofar as it can materially raise farmers' knowledge.

5.3 Grape Quality

After establishing that the farmers watched the videos and that their knowledge increased, we assess whether the intervention improved the quality of their grapes. We examine three objective measures of grape quality: sweetness, count of grapes in a bunch, and the weight of a bunch, which were all measured using a machine. We standardize these measures with respect to the control group means and standard deviations. Table 5 reports the results.

Only the T1 group farmers experience any significant change in the quality of their product. The grapes of T1 farmers are 0.297 SD sweeter than those of control group farmers. While the T2 farmers do not experience any significant improvement in the sweetness of their grapes, we also cannot reject the null hypothesis that the coefficients of T1 and T2 are equal. In terms of the other measures of quality, we do not find any significant changes in the count of grapes in a bunch nor their overall weight.

Interestingly, we find that farmers of both arms believe that their grapes are sweeter. Table A5 shows that training-only arm farmers assess their grapes to be 0.47 SD sweeter than control group farmers, while training and aspiration arm farmers assess their grapes as 0.51 SD sweeter. Here too, we cannot reject the null that T1 and T2 coefficients are equal. T1 farmers also believe that their grape counts are more and their grapes are heavier—although, we cannot reject the null that these metrics are not different from those of T2 farmers.

This suggests that while farmers overestimate how sweet their grapes are, when farmers saw technical videos and aspirational videos together, they overestimated more than the training-only group farmers.

5.4 Farmers' Aspiration

We next assess whether the farmers' aspirations increased after participating in the program. During endline, we collected farmers' aspired income and grape sweetness in three- and five-years time. We use the IHS of aspired income and standardized aspired sweetness as the outcome variables to measure farmer aspirations. We report results in Table 6.

We find at best only weak evidence that the aspirational videos had any impact on farmers' aspiration. The training and aspiration arm farmers experience a slight increase on their aspired sweetness in three years, a 0.19 SD increase in the aspired sweetness (two percent increase relative to control group mean). This is very small and we cannot reject the null that T1 and T2 are equal. We do not find any significant change of farmers' aspirations measured through income or five-year sweetness.

These results suggest that bundling multiple learning objectives when providing farmers training through mobile application may be not as effective as keeping it focused. While the training-only arm and training-and-aspiration arm farmers had access to the same technical content and their share of watching technical videos were similar, only the former group of farmers succeeded in translating the increase in knowledge to increase the quality of their products. In addition, the training-and-aspiration group farmers had only a small increase in their aspiration.

5.5 Additional Grape-Related Outcomes

We do additional analysis on several grape-related outcomes. We report them in Table 7. We first analyze if farmers chose a different variety of grape instead of the predominant *jufeng* variety. We find that the treatment had no impact on the choice of variety. We then explore whether treatment group farmers change the amount of land that they cultivate. We also find no change in the planting area. Moreover, we find no statistically significant impacts on measures of productivity and farm earnings such as grape yield, sales volume, revenue, or price.

We then explore whether the intervention affects grape yield, sales volume, revenue, and price. We do not find any impact on any of these outcomes. Although we do not find sales volume and revenue for either T1 or T2 to be significantly different than the control group, we can reject the null that they are equal between T1 and T2 at a five percent level of significance. It is noteworthy that the point estimates of sales volume and revenue increases for T1 are positive, while they are negative for T2.

The absence of any significant increase in sales revenue or price suggests that without demand side change (branding, connecting with the middlemen), an increased supply of higher quality grapes by a small number of farmers may not be enough to allow the farmers to receive a price premium for their higher quality products.

6 Conclusion

Providing technical training is an important method to facilitate farmers to adopt new technology and better farming practices. We conduct an RCT to test whether technical training can be provided to farmers through mobile application.

We find that mobile-application-based training can reach farmers without incurring large fixed costs associated with traditional forms of agricultural extension. Moreover, our findings show that an app based training can be effective in transferring information. Treatment farmers in our study experience an increase in their knowledge.

We also find that our intervention is effective in translating the transfer of information to improve product quality. Farmers in the training-only arm of our study produced sweeter grapes, although the effect size is relatively small.

While providing training through apps is an effective intervention in transferring information, bundling technical modules with aspirational modules fails to achieve either increasing the quality of products or aspiration. In spite of the relative increase in knowledge, treatment farmers overestimate the quality of their products. Our results show that trying to nudge farmers with aspirational videos leads to these farmers overestimating the quality of their products and contravenes any potential increase in the actual quality of product to be gained from the increased knowledge.

Our findings suggest that using mobile-based training can be an effective alternative to reach many farmers with updated information in a quick and timely manner and at a relatively low cost. Since farmers can watch videos in their own time, these trainings are flexible, do not require constant trainer involvement, and can be scaled up quite easily.

Our findings further suggest that bundling multiple objectives on digitally delivered training is not effective. This suggests that when trainings are provided using ICT, it is desirable that such training modules only focus on one learning objective. Given the relative ease in scaling up such intervention, the apparent necessity to keep a sharper focus poses the tension of scale vs. intensity while considering the modality of delivering training/extension services to farmers—an issue that merits further exploration.

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Tables

Table 1: Baseline Balance Test

	(1)	(2)	(3)	(4)
	C	T1	T2	p-value from test of (1)=(2)=(3)
Farmer Characteristics				
Male (=1)	0.67	0.72	0.70	0.532
Age (in years)	47.80	46.53	47.72	0.175
Completed middle school or above (=1)	0.62	0.67	0.58	0.069*
Has a good health (=1)	0.43	0.46	0.36	0.118
Household size	3.79	3.87	3.80	0.734
Has training experience (=1)	0.31	0.35	0.30	0.583
IHS(Total household income)	11.27	11.61	11.23	0.100*
Years of grape planting	21.50	21.45	21.48	0.999
Grape planting area (acre)	1.74	1.94	1.82	0.347
IHS(Grape yield)	10.92	11.00	11.09	0.617
IHS(Revenue from grape)	9.39	10.41	9.26	0.018**
IHS(Average grape sales price)	1.34	1.34	1.28	0.418
Outcomes Variables				
Test score (standardized)	0.00	-0.09	-0.11	0.523
Self assessed sweetness (standardized)	-0.00	0.07	0.11	0.527
Self assessed count (standardized)	-0.00	0.09	-0.01	0.552
Self assessed weight (standardized)	-0.00	0.23	-0.06	0.058*
IHS(Aspired income in 3 years)	11.37	11.78	11.91	0.119
Aspired sweetness in 3 years (standardized)	-0.00	-0.11	0.08	0.125
IHS(Aspired income in 5 years)	10.21	11.27	10.73	0.125
Aspired sweetness in 5 years (standardized)	-0.00	-0.06	0.08	0.322
N	370	324	332	
Cluster	38	39	39	
p-value from joint test of equality				
C=T1			0.007***	
C=T2			0.149	
T1=T2			0.016**	

Table 2: App Usage

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Used the App (=1)				*App Usage Frequency*				*Minutes Spent*			
	Overall	Placebo Videos	Technical Videos	Aspirational Videos	Overall	Placebo Videos	Technical Videos	Aspirational Videos	Overall	Placebo Videos	Technical Videos	Aspirational Videos
T1	0.360***	0.245***	0.638***	0.000	26.178***	3.806***	22.380***	0.000	115.049***	7.681***	107.378***	0.000
	(0.051)	(0.050)	(0.042)	-	(2.702)	(0.694)	(2.236)	-	(19.843)	(2.371)	(19.006)	-
T2	0.391***	0.246***	0.669***	0.426***	30.524***	4.652***	23.837***	2.034***	107.206***	10.307***	94.666***	2.233***
	(0.036)	(0.039)	(0.029)	(0.036)	(2.658)	(0.795)	(1.826)	(0.335)	(14.450)	(2.375)	(13.605)	(0.433)
Observations	687	687	687	687	687	687	687	687	687	687	687	687
Control-group mean	0.310	0.310	0.004	0.004	2.588	2.478	0.102	0.008	4.368	3.576	0.783	0.010
T1=T2 (p-value)	0.553	0.985	0.549	0.000	0.250	0.365	0.614	0.000	0.749	0.346	0.587	0.000

Notes: These regressions do not include any control variables. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 3: Share of Video Watched by Treatment Arm

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Technical Video					Aspirational Video		
	Overall	May	June	July	August	Overall	May	June
T1	0.222***	0.077***	0.172***	0.295***	0.253***	0.000	0.000	0.000
	(0.019)	(0.012)	(0.017)	(0.026)	(0.027)	-	-	-
T2	0.266***	0.090***	0.188***	0.356***	0.314***	0.093***	0.095***	0.091***
	(0.019)	(0.012)	(0.020)	(0.026)	(0.022)	(0.012)	(0.013)	(0.015)
Observations	687	687	687	687	687	687	687	687
Control-group mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
T1=T2 (p-value)	0.104	0.463	0.554	0.098	0.083	0.000	0.000	0.000

Notes: These regressions do not include any control variables. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 4: Impact on Test Score

	(1) Standardized IRT Score (All 10 questions)	(2) Standardized IRT Score (Repeated 5 questions)
T1	0.541***	0.377***
	(0.100)	(0.096)
T2	0.474***	0.420***
	(0.104)	(0.084)
Observations	687	687
Control-group mean	0.000	0.000
T1=T2 (*p*-value)	0.527	0.577

Notes: All regressions include test score at baseline. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 5: Impact on Grape Quality

	(1) Self-Assessed Sweetness	(2) Machine-Measured Sweetness
T1	0.474***	0.297**
	(0.092)	(0.132)
T2	0.510***	0.099
	(0.086)	(0.109)
Observations	687	679
Control-group mean	0.000	0.000
Raw Control-group mean	17.377	15.920
Raw Control-group SD	1.897	1.327
T1=T2 (p-value)	0.666	0.150

Notes: All outcome variables are standardized with respect to control group. All regressions include self-assessed grape quality at baseline. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 6: Impact on Aspiration

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS(Income)	Sweetness	IHS(Income)	Sweetness
T1	0.103	0.125	0.101	0.101
	(0.080)	(0.107)	(0.089)	(0.095)
T2	0.028	0.186*	0.034	0.095
	(0.094)	(0.107)	(0.094)	(0.096)
Observations	686	684	685	684
Control-group mean	12.215	0.000	12.392	0.000
Raw Control-group mean		18.375		19.197
Raw Control-group SD		1.884		2.230
T1=T2 (p-value)	0.404	0.562	0.475	0.946

Notes: All regressions include outcome variable measured at baseline. Outcome variables in Columns (2) and (4) are standardized with respect to control group. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table 7: Impact on Additional Grape Production-Related Outcomes

	(1) Jufeng Variety (=1)	(2) Planting Area (Acre)	(3) IHS(Yield)	(4) IHS(Sale Volume)	(5) IHS(Revenue)	(6) IHS(Price)
T1	-0.004	-0.031	0.038	0.227	0.265	0.039
	(0.012)	(0.069)	(0.075)	(0.163)	(0.178)	(0.028)
T2	-0.000	0.064	0.032	-0.168	-0.135	0.035
	(0.007)	(0.068)	(0.081)	(0.214)	(0.227)	(0.027)
Observations	687	687	687	687	687	672
Control-group mean	0.988	1.790	11.10	10.74	11.63	1.646
T1=T2 (p-value)	0.742	0.252	0.944	0.015	0.019	0.857

Notes: All regressions include baseline outcome as control variable. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Figures

Figure 1: Study Timeline

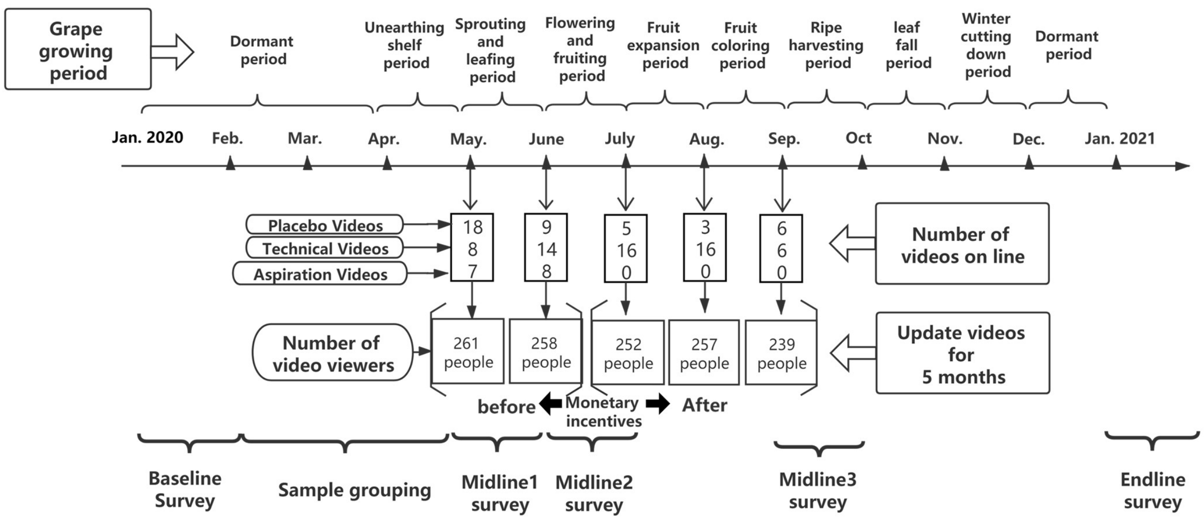
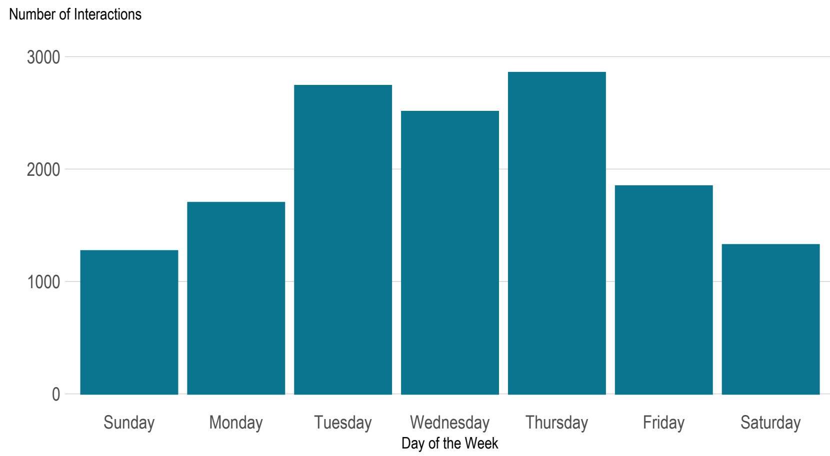
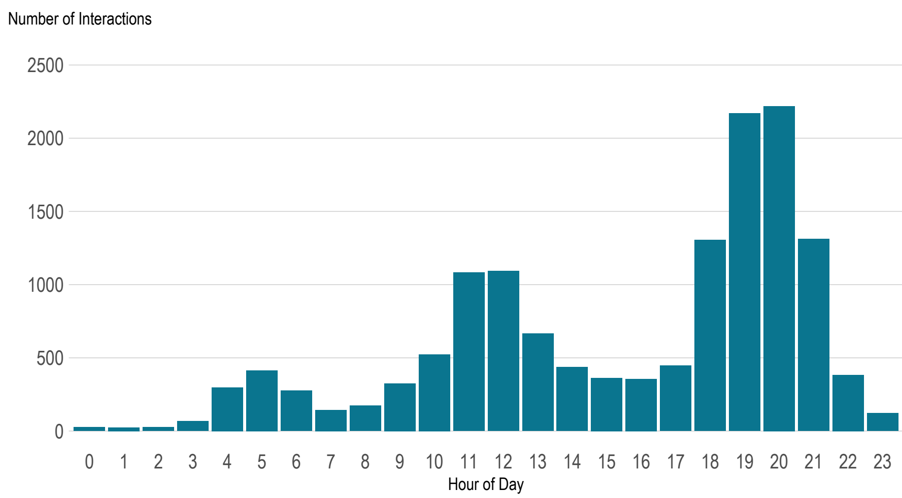


Figure 2: App Interaction Frequency by the Day of the Week



Note: Each interaction with the app is a video click by the user.

Figure 3: App Interaction Frequency by the Time of the Day



Note: Each interaction with the app is a video click by the user.

Appendix A

Table A1: Attrition

	(1) Missing at Midline	(2) Missing at Endline
T1	0.053	0.016
	(0.037)	(0.038)
T2	0.049	0.045
	(0.039)	(0.038)
Observations	1,026	1,026
Control-group mean	0.222	0.311
T1=T2 (p-value)	0.931	0.515

Notes: Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A2: Impact on Raw Test Score

	(1) Standardized Test Score (All 10 questions)	(2) Standardized Test Score (Repeated 5 questions)
T1	0.520***	0.371***
	(0.097)	(0.095)
T2	0.451***	0.413***
	(0.102)	(0.083)
Observations	687	687
Control-group mean	0.000	0.000
Raw Control-group mean	7.380	4.388
Raw Control-group SD	1.532	0.805
T1=T2 (p-value)	0.492	0.572

Notes: All regressions include test score at baseline. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A3: Impact on Other Grape Outcome Measures

	(1)	(2)	(3)	(4)
	Self-Assessed		Machine-Measured	
	Count	Weight	Count	Weight
T1	0.173*	0.213**	0.138	-0.114
	(0.103)	(0.105)	(0.117)	(0.103)
T2	0.039	0.149	0.010	-0.154
	(0.093)	(0.106)	(0.121)	(0.116)
Observations	687	687	679	679
Control-group mean	0.000	0.000	0.000	0.000
Raw Control-group mean	81.784	1.865	68.173	1.659
Raw Control-group SD	20.617	0.439	20.272	0.510
T1=T2 (p-value)	0.202	0.576	0.364	0.720

Notes: All outcome variables are standardized with respect to control group. All regressions include self-assessed grape quality at baseline. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A4: Impact on Agricultural Investments

	(1) Fertilizer Expenditure (IHS))	(2) Labor Expenditure (IHS)
T1	0.112	0.649*
	(0.129)	(0.373)
T2	0.042	0.754**
	(0.134)	(0.349)
Observations	687	687
Control-group mean	9.225	6.098
T1=T2 (*p*-value)	0.525	0.777

Notes: All regressions include baseline outcome as control variable. Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A5: Multiple Hypothesis Testing

	App Only			App+Aspiration		
	Effect	p-value	Sharpened q-value	Effect	p-value	Sharpened q-value
Used App (=1)	0.360***	0.000	0.001	0.391***	0.000	0.001
App Usage Frequency	26.178***	0.000	0.001	30.524***	0.000	0.001
Minutes Spent	115.049***	0.000	0.001	107.206***	0.000	0.001
Standardized Test Score (All 10 questions)	0.541***	0.000	0.001	0.474***	0.000	0.001
Standardized Test Score (Repeated 5 questions)	0.377***	0.000	0.001	0.420***	0.000	0.001
Sweetness (Machine Reported)	0.297**	0.027	0.048	0.099	0.368	0.418
Sweetness (Self Reported)	0.474***	0.000	0.001	0.510***	0.000	0.001
3-year Aspiration IHS(Income)	0.103	0.201	0.277	0.028	0.766	0.584
3-year Aspiration Sweetness	0.125	0.243	0.322	0.186*	0.085	0.147
5-year Aspiration IHS(Income)	0.101	0.260	0.330	0.034	0.720	0.584
5-year Aspiration Sweetness	0.101	0.291	0.360	0.095	0.326	0.396
Jufeng Variety (=1)	-0.004	0.712	0.584	0.000	0.965	0.704
Planting Area (Acre)	-0.031	0.656	0.584	0.064	0.346	0.406
IHS(Yield)	0.038	0.619	0.584	0.032	0.694	0.584
IHS(Sale Volume)	0.227	0.167	0.260	-0.168	0.434	0.465
IHS(Revenue)	0.265	0.140	0.244	-0.135	0.552	0.533
IHS(Price)	0.039	0.160	0.260	0.035	0.206	0.277

Notes: Adjusted sharpened q-values calculated for all outcomes using the method suggested by Anderson (2008) based on Benjamini et al. (2006). *** p<0.01 ** p<0.05 * p<0.1

Table A6: App Usage (Control Variables Picked Using LASSO)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Used the App (=1)				*App Usage Frequency*				*Minutes Spent*			
	Overall	Placebo Videos	Technical Videos	Aspirational Videos	Overall	Placebo Videos	Technical Videos	Aspirational Videos	Overall	Placebo Videos	Technical Videos	Aspirational Videos
T1	0.389***	0.277***	0.665***	0.000	28.428***	4.362***	23.900***	0.000	121.462***	7.343**	113.883***	0.000
	(0.057)	(0.057)	(0.049)	-	(3.730)	(0.914)	(3.040)	-	(22.706)	(2.864)	(21.570)	-
T2	0.415***	0.262***	0.698***	0.434***	30.095***	4.510***	23.628***	1.957***	88.116***	8.332***	77.542***	2.241***
	(0.045)	(0.045)	(0.036)	(0.040)	(2.864)	(0.757)	(2.186)	(0.287)	(17.040)	(2.745)	(16.337)	(0.395)
Observations	687	687	687	687	687	687	687	687	687	687	687	687
Control-group mean	0.310	0.310	0.004	0.004	2.588	2.478	0.102	0.008	4.368	3.576	0.783	0.010
T1=T2 (p-value)	0.678	0.806	0.560	0.000	0.680	0.878	0.932	0.000	0.203	0.777	0.151	0.000

Notes: These regressions include control variables picked by implementing post-double selection method of Chernozhukov et al. (2017). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A7: Impact on Test Score (Control Variables Picked Using LASSO)

	(1) Standardized IRT Score (All 10 questions)	(2) Standardized IRT Score (Repeated 5 questions)
T1	0.432***	0.362***
	(0.092)	(0.102)
T2	0.526***	0.509***
	(0.103)	(0.103)
Observations	687	687
Control-group mean	0.000	0.000
T1=T2 (p-value)	0.342	0.084

Notes: These regressions include control variables picked by implementing post-double selection method of Chernozhukov et al. (2017). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A8: Impact on Grape Quality (Control Variables Picked Using LASSO)

	(1) Self-Assessed Sweetness	(2) Machine-Measured Sweetness
T1	0.494***	0.311***
	(0.097)	(0.119)
T2	0.554***	0.117
	(0.102)	(0.115)
Observations	687	679
Control-group mean	0.000	0.000
T1=T2 (p-value)	0.589	0.117

Notes: All outcome variables are standardized with respect to control group. All regressions include control variables picked by implementing post-double selection method of Chernozhukov et al. (2017). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A9: Impact on Aspiration (Control Variables Picked Using LASSO)

	(1)	(2)	(3)	(4)
	3-year aspiration		5-year aspiration	
	IHS(Income)	Sweetness	IHS(Income)	Sweetness
T1	0.075	0.142	0.063	0.136
	(0.066)	(0.108)	(0.095)	(0.091)
T2	0.025	0.191	0.012	0.192
	(0.065)	(0.117)	(0.077)	(0.104)
Observations	686	684	685	684
Control-group mean	12.215	0.000	12.392	0.000
T1=T2 (*p*-value)	0.435	0.630	0.614	0.625

Notes: Outcome variables in Columns (2) and (4) are standardized with respect to control group. All regressions include control variables picked by implementing post-double selection method of Chernozhukov et al. (2017). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Table A10: Impact on Additional Grape Production-Related Outcomes (Control Variables Picked Using LASSO)

	(1) Jufeng Variety (=1)	(2) Planting Area (Acre)	(3) IHS(Yield)	(4) IHS(Sale Volume)	(5) IHS(Revenue)	(6) IHS(Price)
T1	-0.002	-0.050	-0.039	0.147	0.170	0.010
	(0.011)	(0.062)	(0.053)	(0.150)	(0.169)	(0.022)
T2	0.002	0.051	0.033	-0.130	-0.104	0.034
	(0.007)	(0.061)	(0.058)	(0.202)	(0.221)	(0.021)
Observations	687	687	687	687	687	672
Control-group mean	0.988	1.790	11.10	10.74	11.63	1.646
T1=T2 (p-value)	0.707	0.177	0.204	0.0812	0.112	0.240

Notes: All regressions include control variables picked by implementing post-double selection method of Chernozhukov et al. (2017). Heteroskedasticity-robust standard errors, clustered by zu, in parentheses. *** p<0.01 ** p<0.05 * p<0.1

Appendix B

Figure B1: App Interface

Figure B2: Sweetness Measurement Machine

Figure B3: Sample Coverage and Attrition

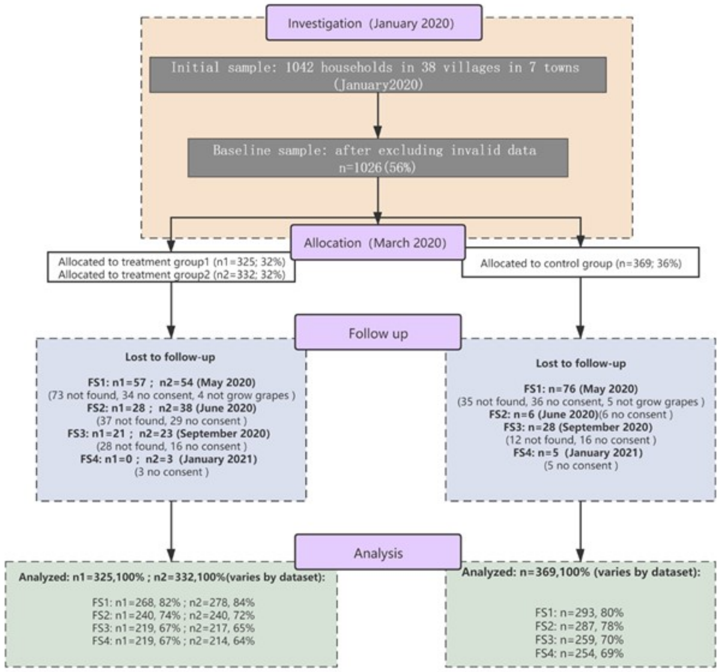


Figure B4: Location of Study Households

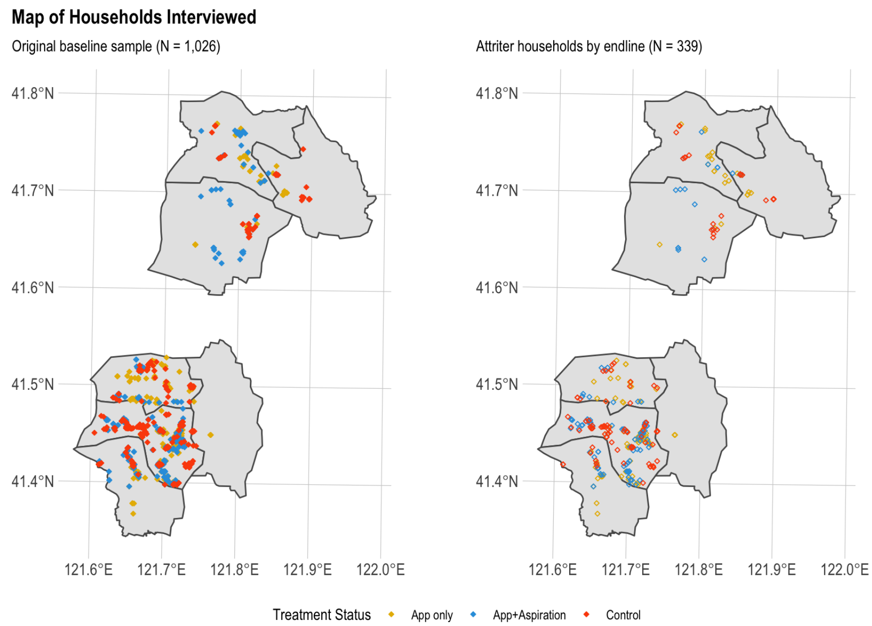
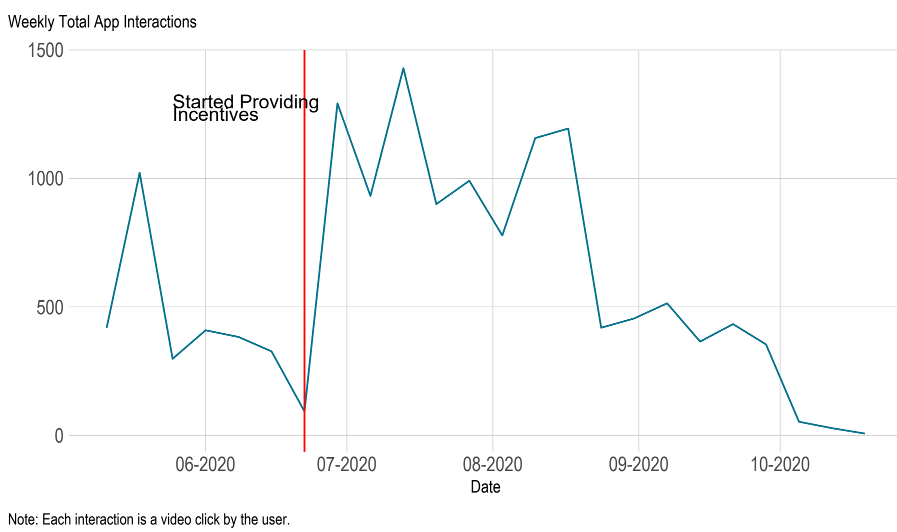


Figure B5: App Interaction Frequency During the Study Period



Appendix C

Topics of Technical Videos

1. **Pruning spike thinning fruit**

    - In order to improve grape quality, the number of bunches is controlled by thinning part of the inflorescence in grape production, and then the inflorescence is shaped, modified and the bunches are adjusted to control the yield, improve the quality, balance the bunches and regulate the shape of the bunches.
    - If the farmers in the experimental group follow the technical video instruction, they will perform bud blotting and branch setting in spring when new shoots are sprouting, and picking, inflorescence thinning and spike pruning when grapes are flowering, which will result in sufficient supply of nutrients needed for grapes, well-proportioned and ventilated fruit clusters, uniform sunlight, satisfying fruit growth, and promoting sugar accumulation under photosynthesis, which will eventually lead to higher grape sweetness and improved grape quality and sales price.

2. **Water and fertilizer management** The crucial "five fertilizations" and "six waterings" of the grape year, along with the growing process, were explained and demonstrated.

    - *Five fertilizer applications*
        - Germinating fertilizer: It is usually applied before the grapes sprout, this time with nitrogen fertilizer, in order to promote neat sprouting, thick leaves and large and strong inflorescences.
        - Expansion fertilizer: This fertilizer is applied after the grapes have set, when the grains are as big as green beans. This time, the fertilizer is mainly nitrogen, with phosphorus and potassium. You can apply high nitrogen compound fertilizer or common three element compound fertilizer, and add nitrogen fertilizer such as urea as appropriate. This time the amount of fertilizer to be large, can account for about 50 percent of the amount of fertilizer applied to the year.
        - Fertilizer for ripening: This is done in two applications 20-30 days before the grapes ripen. Apply a high potassium type water soluble fertilizer, and another application when the grapes start to soften and are not yet colored.

- Moon fertilizer: After the grapes are harvested, a fertilizer is applied immediately, usually 15 kg of water soluble fertilizer (high nitrogen type), which is used not only to restore the tree's potential but also to promote the differentiation of buds and lay the foundation for a good yield the following year.
- Overwintering fertilizer: The traditional method is to apply it when the grapes are dormant. However, our video advocates applying it in August and September, after the grapes have been harvested and while the green leaves are still growing. This is the second peak of the root growth of the grapes, which promotes the production of a large number of fibrous roots to strengthen the tree and make it more conducive to overwintering. This time, the fertilizer is mainly organic, with calcium fertilizer or a small amount of three elements added.

The period of fertilization should be closely related to the growth and development stages of the grapes. If the farmers in the experimental group follow the instructions of the technical video and apply nitrogen, phosphorus, potassium and calcium fertilizers correctly, the budding period can increase the budding rate, enlarge the inflorescence and make the new tips grow strong; the young fruit period promotes the rapid enlargement of grapes, reduces the small fruit rate and promotes flower bud differentiation; the fruit ripening period makes the grapes color complete, the flesh is firm and the fruit powder is uniform, which largely thickens the grape cell wall and increases the concentration of cell sap, thus The final sweetness level is increased.

- *Six irrigation applications*
  - Before the grapes budded. The first critical period is before the grapes sprout. When grapes sprout, the new tips will grow rapidly, inflorescences will develop and the root system will be in a stage of vigorous activity, which is one of the critical periods for grapes to require water. In northern China, during the spring drought, grapes are covered with moist soil for a long time, and when they emerge from the soil, they are not watered immediately and are susceptible to dry winds, resulting in poor budding and even branch draining.
  - About 10 days before flowering. During this period, the new tips and inflorescences grow rapidly, and the root system also starts to produce new roots in large quantities, assimilating vigorously, transpiration gradually increases, requiring more water. When the weather is dry, appropriate watering during

the flowering period can improve the fruit set rate.

- About 10 days after flower drop. About 10 days after flowering is the second critical period. During this period, the new tips thicken and grow rapidly, the base begins to lignify, the leaves increase rapidly, the new inflorescence primitive body forms rapidly, the root system occurs in large numbers of new lateral roots, the root system in the soil to reach the most vigorous degree of water absorption, while the first growth peak of grapes comes, is a critical period of fertilizer and water requirements.
- Fruit coloring period. At this time, the grapes grow very fast and begin to accumulate sugar in the grapes. The new tips thicken and begin to lignify, and the inflorescences develop rapidly. The supply of suitable fertilizer during this period will not only improve the quality of the grapes that year, but will also have a good effect on the next year's yield.
- Fruit ripening period. Generally in areas where irrigation or moisture retention is good, soil moisture is sufficient. If there is insufficient rainfall, poor soil water retention, or large fertilizer application then irrigation is required. With proper soil moisture during grape ripening, fruit development is good, yield is high and sugar content is also high. If the moisture is large, the grapes can also ripen well, but the sugar content is reduced, the fragrance is reduced, easy to crack the fruit, and not resistant to storage.
- When grapes are buried in the soil to prevent cold. If the soil is dry, it is inconvenient to bury the soil, and a small amount of watering is needed before burying. In northern China, in winter and spring drought areas, it is customary to pour freezing water in winter.

Grapes have a strict water requirement and it is strictly forbidden to flood them. They require more water during the early growth period or the nutritional growth period and less water during the late growth period or the fruiting period, avoiding rain and dew. Therefore, we highlighted in the video that irrigation is applied 5-7 times during the budding period, before and after flowering, before and after grape expansion and 6 times after harvesting, depending on the soil conditions, the number of irrigation can be increased appropriately. If the farmers in the experimental group followed the instructions in the technical video and controlled the water content according to the characteristics of the grapes during each reproductive period, they were able to meet the normal requirements of water content for grape growth and development and fruit expansion. This will promote healthy maturation of the plant, reduce the occurrence of cracking, rotting and dropping of fruit, appropriate soil moisture for grapes, good fruit development, high yield and high sugar content.

3. **Pest control** Pests and diseases of grapes have a great impact on the growth and development of the grape plant and its yield quality. Especially in rainy areas and in years when they encounter a lot of rain, they bring significant losses to grape production. The wide variety of grape pests and diseases and their complex patterns of occurrence make it more difficult to control them. Therefore pest and disease control is also a key element in our technical videos.

   In the video, we suggest that "prevention is the main focus and integrated control" is the basic principle of grape pest and disease control. In grape production, it is important to observe the dynamics of the epidemic and prevent it in advance. Even if the epidemic has not yet occurred, it should be protected by spraying in advance. In order to improve the yield and quality, protect the environment and people's health, it is reasonable to use chemical pesticide control, biological control, physical control and other measures to control pests economically, safely and effectively.

   In the video, we explain four types of control measures.

   - Biological control. It mainly includes the treatment of insects by insects, bacteria and fungus. Biological control is safe for fruit trees and humans and animals, does not pollute the environment, does not harm natural enemies and beneficial organisms, and has the effect of long-term control. At present, the agricultural anti 402 biopesticide applied in production is applied at the root cancer tumor after excision, which has a good effect of disease prevention.
   - Physical control. The use of fruit tree pathogens, pests to temperature, spectrum, sound and other specific response and tolerance, kill or repel pests. For example, the current production of non-toxic seedlings advocated that is the use of heat treatment methods to remove the virus.
   - Chemical control. Application of chemical pesticides to control the occurrence of pests and diseases, is still the main means of pest control, is also an important and indispensable part of integrated control. Although chemical pesticides exist to pollute the environment, kill natural enemies and residual toxicity and other problems, but it has the advantages of fast, effective, easy to use.
   - Agricultural control. Keep the fields clean, remove the diseased branches and leaves and the diseased fruits and spikes, and bury them deeply or destroy them

to reduce the source of the disease and mitigate the damage in the following year; tie the vines, pick the heart and remove the secondary tips in time to improve the ventilation and light conditions on the shelf, which can reduce the damage of the disease and insects; strengthen the fertilizer and water management to enhance the tree potential, which can improve the ability of the plant to resist diseases and insects; apply more organic fertilizers, increase phosphorus and potassium fertilizers, and use less chemical nitrogen fertilizers, which can make the grapes grow strong and reduce the disease. The plant will grow strong and reduce diseases; remove weeds in time to eradicate the living environment and overwintering sites of pests and diseases.

Integrated pest and disease control technology is the key to pollution-free grape production, so farmers in the experimental group need to understand more about the pests and diseases that infect grapes, prescribe the right remedy, strengthen the management of soil and planting environment, regularly amend the grape orchard, and fill, burn, and cut diseased branches to effectively promote grape growth and development, increase fruit size, and improve fruit quality.