Mixed Evidence: Combining Field Days and Digitally Provided Information to Train Palm Farmers in the Amazon *

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March 21, 2025

Abstract

Research suggests that digital information provision is a cost-effective substitute for in-person agricultural extension in hard-to-reach locations in developing countries. However, we have little evidence on whether and the extent to which these two modes of agricultural training are complementary. This paper uses a 2×2 field experiment involving 944 palm farmers in two Ecuadorian provinces in the Amazon to compare the effects of in-person field days, digital nudges, and their combination on engagement with automated messaging campaigns and personalized reports and on a variety of agricultural outcomes. Our results indicate positive impacts of the field days on engagement with the automated messaging campaigns, farmer knowledge, and palm plantation expansions in low-conservation-value areas within the farmers' plots. The nudges were successful in inducing engagement with specific learning content, such as personalized reports.

Keywords: agricultural extension platforms, digital engagement, economic development.
JEL codes: M53, N56, O13, Q16.

*Ethical approval was obtained from the Office of Research Compliance at the University of Notre Dame (IRB Protocol Number 24-05-8600). This study is registered in the AEA RCT Registry, and the public URL for the trial is here: https://www.socialscienceregistry.org/trials/13685. For useful comments, we are grateful to Eric Auerbach, Andrew Dillon, Sarah Janzen, Christopher Udry, and conference participants at the GPRL-IPA Researcher Gathering 2024. We acknowledge financial support from the Inter-American Development Bank and the Pulte Institute of the University of Notre Dame. Daniela Castillo, Jack O'Leary, and Carlos Albuja-Jijon provided outstanding research assistance. All errors are our own.

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1 Introduction

Information provision through mobile phones is a promising tool for the delivery of agricultural advice in developing countries (Fabregas et al., 2019). It has been found to have modest yet positive effects on SMS engagement (Camacho and Conover, 2019), farmer knowledge and adoption of recommended practices (Cole and Fernando, 2021; Fabregas et al., 2024; Fafchamps and Minten, 2012; Fu and Akter, 2016; Larochelle et al., 2019; Van Campenhout et al., 2017), agricultural yields (Arouna et al., 2021; Casaburi et al., 2014), and market performance (Courtois and Subervie, 2015; Nakasone, 2013). Such findings support the view that mobile phone technologies are a cost-effective substitute for in-person agricultural extension, which is generally regarded as prohibitively expensive (for a discussion, see Fabregas et al., 2022). However, the *complementarity* of in-person agricultural extension and mobile phone-based informational campaigns remains a largely understudied topic.[1]

There are good reasons to believe that in-person agricultural extension could improve the effectiveness of informational campaigns delivered through mobile phones. First, field days could be used to educate farmers about mobile phone usage to prevent digital illiteracy from rendering text messages ineffective.[2] Second, live demonstrations by *local* extensionists during field days could boost social learning and reduce indirect learning frictions and inefficiencies (BenYishay and Mobarak, 2019; Emerick and Dar, 2021; Kondylis et al., 2017). Third, in-person interactions between local agricultural extentionists and farmers could be used to establish trust in digitally transmitted advice, as has previously been shown to be crucial for farmers to act upon recommendations (Cole and Sharma, 2017; Fishman et al., 2016).

Conversely, there are good reasons to believe that information provision through digital means could perform better than in-person agricultural extension in drawing the attention of farmers to specific pieces of learning content. For example, digital nudges can help ensure future events stay "top of mind" for inattentive decision-makers (Karlan et al., 2016), and automated information systems can seamlessly personalize and convey recommendations to farmers (Athey et al., 2023). Therefore, whether and to what extent in-person agricultural extension services and digitally provided information complement each other is a propitious subject for empirical investigation.

This paper studies the causal impact of in-person field days and digital nudges on engagement with a series of automated informational campaigns delivered through WhatsApp and on farmers' knowledge, adoption of recommended practices, productivity, and environmental

[1] Previous studies have focused on live phone calls as add-ons to SMS-based agricultural extension (Cole and Fernando, 2021; Fabregas et al., 2024).

[2] In a review article, Nakasone et al. (2014) argue that farmers may need a high level of ability or literacy to process the content of agricultural informational campaigns.

conservation in the context of oil palm agriculture in the Amazon. The empirical strategy of the study consists of a field experiment involving 944 palm farmers in Ecuador's Orellana and Sucumbíos provinces and conducted in July–September 2023. The experiment participants were enrolled in a messaging service delivering personalized reports and automated informational campaigns about sustainable practices across 4 topics: palm nursery and environmental conservation, pollination, fertilization, and integral pest management.

The experiment assigned farmers to the control group, to one of two treatments, or to a combination treatment in a factorial or 2×2 design. The first treatment consisted of a series of field days involving (1) classroom learning and live demonstrations of each campaign's recommended agricultural practices and (2) a tutorial explaining how to use the WhatsApp messaging service to interact with the automated messaging service. The second treatment featured, for each campaign, an anticipatory WhatsApp nudge, designed on the basis of insights from the behavioral economics literature, to draw the farmers' attention to a personalized report containing plot-level recommendations.

The Ecuadorian Amazon offers an ideal laboratory for us to investigate engagement with digital information provision services in agriculture and the impacts of agricultural extension on the adoption of sustainable practices. First, in contrast to sub-Saharan Africa, Latin America has smartphone adoption rates of close to 70 percent (GSM Association, 2020), such that agricultural information can be transmitted via WhatsApp (an instant messaging and voice-over-IP service capable of sharing images, documents, hyperlinks, and locations) instead of SMS services, which are generally limited in scope to the transmission of 160-character text messages. For the purposes of this study, WhatsApp allowed us to construct more complete engagement indicators, including read, reply, and click rates, than would have been possible with SMS services. Second, forest and agricultural income constitutes more than 50 percent of total household income in the Ecuadorian rainforest (Luna et al., 2020), highlighting that productivity improvements could reduce poverty in the region. Third, and relatedly, the environmental externalities associated with successful transmission of information supporting the adoption of sustainable agricultural practices are potentially greater in the Amazon than anywhere else in the world given that the Amazon—the world's largest tropical rainforest—has experienced fast agriculture-related deforestation in the recent past (Lapola et al., 2023).

To measure impacts, this study leverages several data sources, including the log file of a mobile platform extracting data from the WhatsApp messaging service, survey data, and satellite imagery. The log file data record all interactions of farmers with the messaging campaigns, enabling us to construct indicators for message-level reading and response rates and file-downloading and link-clicking rates. Both surveys contain knowledge questions designed to assess learning from key technical lessons on the topics of the messaging campaigns and

a battery of questions designed to measure self-reported agricultural practices at the farmer level and crop productivity at the plot level. Finally, two rounds of satellite imagery were gathered simultaneously with the study surveys, allowing us to detect palm area changes with standard deep learning classification algorithms, palm health changes with standard vegetation indexes such as the normalized difference vegetation index (NDVI), and palm overlap with high-conservation-value (HCV) areas previously mapped by the United Nations.

We find that the field days increased automated message reading, response, and click rates by 12, 90, and 52 percent, respectively, while the behavioral nudges increased the click rate on personalized reports by 238 percent but had no impact on engagement with other digital content. However, only the field days improved tested knowledge, with attendance of the full program of field days raising knowledge index values by 36 percent. We interpret these findings as a strong indication that in-person interactions can enhance digital engagement with general learning materials while nudges can boost digital engagement with specific learning materials.

In line with the previous literature reviewed by Suri and Udry (2022), we find no indication of impacts on the adoption of recommended agricultural practices or productivity. However, we find that the field days expanded palm plantations by 12 percentage points relative to plot size, with this impact concentrated in low-conservation-value (LCV) areas within farmers' plots. We take these findings as suggestive that training can serve as a policy tool to improve farmer livelihoods by fostering existing agricultural activity while having no further deforestation impacts.

This paper contributes to the literature on digital agricultural extension in developing countries, which is too vast to describe in detail in this article but is extensively reviewed in Aker et al. (2016), Baumüller (2018), and Fabregas et al. (2019). While it is commonly argued that in-person field days represent a much less cost-effective alternative than informational campaigns delivered through mobile phones, we know of no previous study documenting the effects of adding in-person field days to digital informational campaigns. This is a sizable gap in the research, considering that cost reductions associated with digital information provision are expected to arise from scale economies while information has been found to be most effective when adapted to the local context and demonstrated in person, as previously discussed.

Our study also contributes to the online and hybrid education literature, which finds that educational programs imparted exclusively through digital means are less effective than in-person programs (Ahn and McEachin, 2017; Heppen et al., 2017; Xu and Jaggars, 2013; Hart et al., 2018; Figlio et al., 2013; Joyce et al., 2015; Alpert et al., 2016; Bettinger et al., 2017; Krieg and Henson, 2016; Cellini and Grueso, 2021) but that hybrid and in-person programs are equally effective (Kozakowski, 2019; Bowen et al., 2014; Alpert et al., 2016; Cacault et al., 2021); these works cite low student take-up and engagement rates as the root cause of the lower effectiveness of digital than of in-person education. We know of no other study in this literature that

leverages microdata from a mobile platform to examine the impacts of in-person interactions on different measures of digital engagement, including reading, response, and click rates, and that explicitly tests the mechanisms through which the in-person education enhances engagement with digital educational content.

Finally, this paper adds to the economic literature on sustainable oil palm agriculture. A high-yield and high-demand monocultural crop that tolerates many soils, oil palm has lifted millions out of poverty in producer countries (Edwards et al., 2019). However, its environmental impacts are overwhelmingly negative: First, its profitability constitutes a powerful incentive for forest replacement, which in turn causes increases in greenhouse emissions and plant and mammal diversity losses; second, it attracts fruit-predating and reproduction-impeding pests (e.g., beetles) and threatens soil health and water quality because of the associated use of chemical fertilizers and pesticides (Meijaard et al., 2020b). Thus far, the economic literature has addressed this apparent poverty–sustainability trade-off by modeling the market incentives generated by palm certification (e.g., Hsiao, 2021). Our study is the first in this literature to find a positive effect of provision of conservation information to smallholders. The relevance of this finding extends beyond oil palm agriculture, as the same poverty–sustainability trade-off applies to other vegetable oil crops, including soy and coconut (Meijaard et al., 2020a; Green et al., 2019).

The remainder of the paper is structured as follows. Section 2 explains the institutional framework that underlies the design and execution of the field experiment. Section 3 describes in detail the field days and behavioral nudges. The experimental design, including the randomization procedure and timeline, are described in Section 4. Data sources are discussed in Section 5. We demonstrate the quality of our randomization procedure and test for treatment contamination in Section 6. Next, we review the causal impacts of our experimental treatments on digital engagement in Section 7, on knowledge and adoption of recommended practices in Section 8, and on productivity, palm area, and conservation in Section 9. Section 10 offers policy implications and concludes.

2 Contextual Information

The field experiment resulted from a memorandum of understanding (MoU) between IDB Invest—the private-sector arm of the Inter-American Development Bank Group—and the United Nations Development Programme (UNDP)—the managing agency of the Global Environmental Facility (GEF), which finances the implementation of the Comprehensive Amazon Program for Forest Conservation and Sustainable Production (PROAmazonía). The MoU envisaged a technical assistance program for 944 small palm farmers in the provinces of Orellana

and Sucumbíos in Ecuador (see Figure A.1 in Appendix A).

The technical assistance program comprised two components: (1) the implementation of farmers' field schools funded by the UNDP and (2) the deployment of a two-way mobile communication platform, called SatAgro, funded by IDB Invest. This platform is capable of sending personalized messaging campaigns to predefined lists of recipients through a WhatsApp chatbot, including messages with images, video capsules, documents, and hyperlinks. Additionally, the platform can track recipients' engagement with individual message contents and send engagement-dependent follow-up messages to recipients.

To deploy SatAgro, local agricultural engineers designed text messaging campaigns on (1) palm nursery and environmental conservation, (2) pollination, (3) fertilization, and (4) integrated pest management (IPM). Each campaign consisted of an automated sequence of text messages containing advice on specific agricultural practices, images, PDF attachments, and hyperlinks to relevant websites. To improve engagement tracking, most messages included multiple-choice questions about the message's content at the end, to which recipients could reply by typing their selected choice on WhatsApp's messaging line. These campaigns were delivered to local palm farmers in July–September 2023. A final satisfaction survey was sent after the messaging campaign on IPM.

The component messages were crafted on the basis of insights from the behavioral economics literature to maximize engagement, as shown in Figure A.2 of Appendix A. First, the text messages highlighted the personal financial gain associated with the agricultural practices covered in the informational campaign. Second, the recommendations were relayed through simplified heuristic rules, with technical content kept to a minimum. Third, interactive engagement was fostered through the inclusion of buttons, keywords, and links to external materials and personalized reports. Fourth, to increase its salience, important text was highlighted in bold, decorative emojis were placed in every text message, and exclamation marks were used around motivational phrases. Fifth, the messages were personalized with each farmer's name. Finally, to minimize reader fatigue, the number of messages was limited to 7 per campaign, and the length of each text message was limited to 200 words.

Campaign recipients were identified through an agricultural census of Orellana and Sucumbíos palm farmers conducted by a local cadastral surveying company in May 2023. The recipients' identities were verified through an initial text message that asked for a personal ID number given out to the farmers as part of the agricultural census. Afterward, a second text message elicited informed consent on the part of the farmers, and an opt-out option, which respondents could activate by typing "STOP" on WhatsApp's messaging line, accompanied all text messages.[3] The platform responded to the recipients' answers to automated multiple-choice

[3]WhatsApp also allows recipients to block or silence message notifications from specific senders.

text messages by acknowledging their answers and sending them the subsequent message (if any) in the campaign. If an invalid answer was recorded, a message requesting clarification was sent. If the recipient waited more than 4 hours to respond, the subsequent campaign message was automatically sent.

Each automated messaging campaign included one personalized PDF attachment embedded in the middle of the text message sequence. We followed the four-step procedure depicted in Figure A.3 of Appendix A to produce these reports. First, we retrieved all publicly available satellite images at a resolution of 10 m/pixel for the entire study region at baseline from the Sentinel 2A and Sentinel 2B satellites of the Copernicus program of the European Space Agency (ESA). Second, we implemented a supervised classification algorithm trained by means of ground observation for a training set of plots to detect palm areas. Third, using customary vegetation indexes, such as the NDVI, and other layers of information, such as a map of HCV areas elaborated in 2018 by PROAmazonía, we calculated index values and recommendations for each palm area of each farmer's plot in our experimental sample. Finally, we wrote tables containing ordinal scales with descriptors to aid farmers' reading comprehension.

The personalized reports included a map of HCV forest areas within the recipient's plot, a micronutrient diagnosis, fertilizer mix recommendations for the farmer's plots, and a palm health assessment calculated from NDVI values. See Figure B.1 of Appendix B for documentary evidence of the personalized PDF reports.

3 Behavioral Nudges and Farmer Field Days

The behavioral nudges consisted of a single text message per campaign, sent before the campaign's messages to bring to the recipient's attention the personalized PDF reports and the future delivery date of campaign information. Each nudge included (1) a link to the campaign's personalized PDF report with plot-specific information and (2) the release date of the messaging campaign. Figure A.4 in Appendix A reproduces the nudges for the 4 messaging campaigns.

The field days were a series of 4 in-person workshops on the same topics as the messaging campaigns. Each workshop lasted six hours and consisted of a combination of classroom lectures[4] and live field demonstrations imparted by 3 local agricultural engineers. Farmers assigned to this treatment were sorted into one of 18 small groups of 25 farmers or fewer to receive treatment in one of 7 possible locations within a three-month window from April to June 2023. Geospatial analysis was used to calculate the road distance between each farmer's plot and the 7 training venues to assign them to their closest location (see Figure A.5 of Appendix A for a map of the training venues). Within each training venue, groups were randomly assigned

[4] See Figure B.2 in Appendix B for documentary evidence of the classroom activities.

to preset workshop calendar dates on the basis of the engineers' availability (see Table A.3 in Appendix A for the workshop calendar). Each farmer received a telephone invitation and text message reminders detailing her assigned field school dates and venue. Farmers who attended all 4 workshops received a diploma (see Figure B.3 of Appendix B).

Field demonstrations of agricultural practices were a key component of the workshops (see Figure B.4 in Appendix B for documentary evidence). The palm nursery and environmental conservation workshop included demonstrations on substrate handling, cover cropping, seed sowing, irrigation, phytosanitary controls, weed control, shade management, and plant selection. It also included a practical explanation of Ecuador's forest conservation strategy for the implementation of the REDD+ framework[5] from the Paris Agreement and guidance for the identification of HCV forest areas within each farmer's plot to prevent palm-related deforestation. The pollination workshop included demonstrations of pollinator mix elaboration and raw material selection, inflorescence recognition, and pollen application. The fertilization workshop included demonstrations of soil sampling, fertilizer dosage calculation and application, and purchasing and storage practices. Finally, the IPM workshop included field demonstrations of diseased plants and weed removal, pest detection, trap elaboration, and usage of biological and chemical controls.

Additionally, the palm nursery and environmental conservation workshop included a live tutorial to help farmers understand how to read and reply to WhatsApp messaging campaigns, open external links, download attachments, and respond to surveys (see Figure B.5 in Appendix B for documentary evidence). A key activity in this tutorial involved comparing a printout of the personalized report with the PDF file linked in the first messaging campaign.

4 Experimental Design

To uncover the causal impact of farmer field days and behavioral nudges on agricultural outcomes, we use the field experiment described above involving 944 palm farmers in Ecuador's Orellana and Sucumbíos provinces, who owned and managed 1,068 plots in May 2023. These farmers represent 95 percent of the farmers identified in the agricultural census for the two provinces, the remainder of whom did not participate in the study because we were unable to reach them after the census. We formally test for observable differences in outcomes at baseline between the farmers in the experimental sample and nonparticipating farmers in Table A.1 of Appendix A. While the existence of unobservable correlates of availability cannot be ruled out,

[5] REDD stands for "reducing emissions from deforestation and forest degradation in developing countries." The "+" stands for additional forest-related activities that protect the climate, such as sustainable management of forests and the conservation and enhancement of forest carbon stocks.

we fail to find any significant differences in observables between the two groups.

The field experiment involved a factorial design whereby participating farmers were randomly assigned, in equal proportions, to the control group, the field days treatment, the behavioral nudges treatment, or both treatments. Importantly, everyone in our sample, including the control group members, received the automated messaging campaigns to enable estimation of the campaigns' impacts on farmer digital engagement.

Randomization was stratified by the farmers' nearest training venue, the size of the largest plot that they owned, and their engagement with a test message sent through SatAgro before the experiment. This stratification strategy yielded the 28 strata shown in Table A.2 of Appendix A. We implemented the random assignment by means of a computer program to ensure replicability by setting the program's seed to the randomly chosen number 766742, as specified in the trial plan available in the AEA RCT registry. Finally, the randomization was clustered at the farmer level, as treatment spillovers could occur for the 228 plots owned by the 104 multiplot farmers in our sample.

Our randomization resulted in 251 out of the 944 participating farmers being assigned to the control, 227 being assigned to the field days treatment, 243 being assigned to the behavioral nudges treatment, and 223 being assigned to both treatments. In terms of plots, randomization resulted in 278 out of the 1,068 plots being assigned to control, 252 being assigned to the field days treatment, 290 being assigned to the behavioral nudges treatment, and 248 being assigned to both treatments.

The timeline for implementation was as follows. Pre-treatment activities were conducted from 2019 to July 2023. These included telephone interviews with a small number of local farmers to elicit training needs in 2019, the development of messaging campaigns by agricultural engineers in 2022, the implementation of the agricultural census in May 2023 and the baseline survey in June 2023, and farmer randomization in July 2023. Post-treatment activities included only the administration of the study's endline survey in June 2024.

The timeline for the experimental treatments is illustrated in Figure A.6 of Appendix A. The messaging campaigns and experimental treatments were rolled out from July to September 2023. For each campaign topic except the first, the field days treatment was administered before the anticipatory nudge treatment, followed by the messaging campaign. In contrast, the first nudge was sent *after* the regular messaging campaign to ensure that we did not trigger farmers' skepticism by sending them a personalized message before they had become familiar with the automated messaging campaigns.

The field experiment tested three main hypotheses that make up our theory of change. The first is that the in-person interactions would increase farmer engagement with the digital informational campaigns. We posit that the field days should have improved farmer engagement

through the instructors' demonstrations of the chatbot functioning and the field demonstrations of recommended practices, which in turn reduced digital learning frictions. Moreover, we hypothesize that the field days established trust in the automated messaging campaigns as a legitimate source of information.

The second hypothesis is that the behavioral nudges would serve to draw the attention of farmers to specific pieces of digital information. Specifically, we hypothesize that our nudges should have raised engagement with the personalized PDF reports by increasing their salience without having the same effect on engagement with the other automated campaign content.

The third hypothesis is that the digital engagement improved agricultural outcomes. Our rationale for expecting such an improvement is that both the field days and the behavioral nudges are likely to have increased the farmers' knowledge of recommended practices, in turn leading to their adoption, ultimately improving environmental conservation and increasing productivity.

5 Data Sources

We use several data sources to estimate the treatment effects on field day attendance, digital engagement, agricultural knowledge, practice adoption, productivity, and environmental conservation. The paragraphs below discussion the relation of individual datasets with the study's primary and secondary outcomes.

Field day attendance lists.- To keep track of the field day treatment take-up, we leverage mandatory registration lists used by the agricultural engineers to verify the identity of the field day attendants. These lists preclude measurement error, as proof of identity and phone number verification were required by the engineers on the day of each workshop for participation.

SatAgro log file.- To measure farmer engagement with our automated messaging campaigns and nudges, the study leverages the log file of our mobile communication platform, which extracts data from WhatsApp to construct message-level reading indicators, response indicators to the post-message questions sent to farmers, and clicking indicators for the links in each message of the 4 messaging campaigns.

Baseline and follow-up surveys.- To keep track of knowledge acquisition, recommended practice adoption, and productivity, we use data from the baseline and follow-up study surveys. The surveyed information includes demographics; smartphone ownership, broadband internet access, and WhatsApp usage; agricultural productivity, as measured by the harvest in

tons, sales prices, and number of harvest days in the last quarter; total production costs; 26 closed questions on agricultural practices regarding palm nursery, pollination, fertilization, and IPM; 6 questions pertaining to environmental conservation, such as knowledge of Roundtable on Sustainable Palm Oil (RSPO) certification protocols; and 11 open knowledge questions.

Cadastral census and satellite imagery.- To construct objective measures of palm area, environmental conservation, and palm health at the plot level, we first leverage the plot demarcations imposed as part of the cadastral census of May 2023 and georeference them. Then, we use two rounds of satellite imagery corresponding to May 2023 and May 2024 from the ESA and apply a standard classification algorithm to detect palm plantations. We then calculate the intersection of each palm plantation with HCV areas from the PROAmazonÍas 2018 map and calculate standard palm health indexes based on the detected palm areas' NDVI values.

6 Randomization Quality and Field Day Attendance

We begin our empirical analysis by providing evidence of adequate randomization in Table A.4 of Appendix A, which reports the means and standard errors of the key farmer and plot characteristics across our four experimental groups at baseline. The mean age of the farmers in the control group is 45, and only 20 percent of the farmers are women. Regarding digital engagement, the log file of our mobile platform indicates that only 57 percent of the farmers in the control read an initial test text message that we sent them through the platform's chatbot. The mean plot area is 29.7 hectares, out of which 14.4 hectares are identified as palm plantations by our deep learning algorithm. When testing the null hypothesis of equality of means across the four groups, we are unable to reject it at conventional significance levels for any of these variables, indicating that the randomization was successful.

We then report field day attendance rates by topic in Table A.5. Attendance rates in the field days treatment group range from 18.6 percent for the nursery workshop to 72.9 percent for the IPM workshop, indicating substantial noncompliance. The group assigned to receiving nudges on top of the field days displays similar attendance rates. While only farmers assigned to the field days treatment were invited through a telephone call to attend the four workshops, there is also significant evidence of group contamination, as attendance rates for the control group members range from 3.7 percent for the nursery workshop to 16.5 percent for the IPM workshop, with similar noncompliant behavior for the nudges-only group. Thus, in what follows, we report intention-to-treat (ITT) effects and present only two-stage least squares (2SLS) estimates whenever relevant to disentangle the impacts of field day attendance and nudges on knowledge, adoption of recommended practices, and palm growing on the extensive margin.

7 Impacts on Digital Engagement

The log file of our mobile platform records all interactions of farmers with the messaging platform, enabling the construction of message-level reading and response indicators and file-downloading and link-clicking indicators for both the automated messaging campaigns and personalized reports. We estimate via ordinary least squares (OLS) the ITT effect of each treatment and their combination on the indicator Y_{im} of individual i's engagement with the message or interaction opportunity m, given by β_1, β_2, and β_3, in the following linear regression model:

$$Y_{im} = \alpha + T1_i\beta_1 + T2_i\beta_2 + [T1_i \times T2_i]\beta_3 + \gamma_{c(m)o(m)} + \mathbf{X}_i'\boldsymbol{\delta} + \varepsilon_{im}, \tag{1}$$

where $T1_i$ takes value 1 if farmer i was randomly assigned to the field days treatment and 0 otherwise, $T2_i$ indicates assignment to the behavioral nudges treatment, and $\mathbf{X}_i$ is a vector of strata dummies. The parameter $\gamma_{c(m)o(m)}$ is a campaign×order fixed effect, which controls for campaign-specific factors (such as reader fatigue) that affect all farmers' engagement with message m equally on the basis of its order o within messaging campaign c. While including campaign×order fixed effects and strata dummies as controls in the regression is not necessary, their inclusion reduces the residual variance and improves estimation accuracy. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the farmer level. Finally, throughout our exposition of the regression estimates, the estimation sample excludes 7 farmers for whom the log file indicates failed delivery of the messaging campaigns.

We first present the results on digital engagement with the automated messaging campaigns in Table 1. Based on the results for the comparison group from each regression, the farmers assigned to the control group read 61.7 percent of all the text messages, responded to 5 percent of all the response prompts, and clicked on 2.7 percent of all supplied links. Most studies assume that farmers read messages since researchers who use SMS (instead of WhatsApp) do not have log files. Thus, it is hard to know how our numbers compare. However, self-reported information collected through surveys in other studies implies take-up rates in designs featuring SMS campaigns ranging from 9.3 percent (Cole and Fernando, 2021) to 18 percent (Camacho and Conover, 2019); our message reading rates are much higher and clicking rates are lower.

Regarding the experimental impacts, our results indicate that the field days had a strongly significant effect of 8.3 percentage points on message reading rates (p=0.009), or 12 percent relative to the outcome for the comparison group. We also find that the field days had a strongly significant impact of 4.5 percentage points on the prompt response rate (p=0.002), or 90 percent relative to our estimate for the comparison group. Similarly, they had a positive, albeit nonsignificant, impact of 1.4 percentage points (p=0.101), or 52 percent, on the link-clicking rate. In contrast, the behavioral nudges had no statistically significant impact; nor did the com-

bination of the field days with nudges.

We now report the results on respondents' engagement with their personalized reports in Table 2. While all the farmers received one personalized report per topic, the links to these reports were embedded in the middle of each messaging campaign. Since the nudges contained direct links to the personalized reports, we expect the nudges treatment to have increased report-clicking rates. In contrast, only the first field day made the personalized report more easily accessible to farmers through the WhatsApp tutorial, so we expect the field days treatment to have had no impact on the farmers' probability of opening their personalized reports after the first campaign. Indeed, the nudges treatment increases the probability of the respondent's opening the personalized report by 8.1 percentage points (p=0.000), or 238 percent relative to the comparison mean, whereas the field days treatment and the combination of the nudges and field days has no statistically significant impact.

8 Impacts on Knowledge and Adoption of Recommended Practices

As mentioned in the data section, our endline survey included 11 open questions designed to assess farmer knowledge and 26 yes/no questions about the adoption of recommended agricultural practices. We construct knowledge and practice adoption indexes at the topic level using these questions. To calculate the knowledge index for each topic, we leverage the fact that the ideal answer to each open question had several parts, which the surveyors did not prompt the farmers about. Specifically, we first calculate the ratio of the number of correct answers provided by the farmer to the total number of parts of each question's ideal answer, and then we take the average of the resulting ratios across all questions on the same topic. For the construction of each practice adoption index, we simply calculate for each topic the share of recommended practices adopted by the farmer.

We estimate the ITT effects of treatment assignment on the post-treatment index value Y_{ic} of farmer i for topic c, given by the parameters β_1, β_2, and β_3 in the following regression model:

$$Y_{ic} = \alpha + T1_i\beta_1 + T2_i\beta_2 + [T1_i \times T2_i]\beta_3 + \gamma_c + \mathbf{X}_i'\boldsymbol{\delta} + \varepsilon_{ic}, \tag{2}$$

where γ_c is a fixed effect that captures topic-specific factors that affect the knowledge and practice adoption of all farmers equally, such as topic difficulty, and the rest of the variables are defined as in Equation (1). Standard errors are robust to heteroskedasticity of unknown form and are clustered at the farmer level. Finally, to prevent the WhatsApp tutorial delivered during the first field day from biasing our estimates of the impact of the field days, we exclude the first

topic from estimation.

Importantly, noncompliance with treatment assignment, coupled with the contamination in the take-up of field days by farmers originally assigned to the control, complicates the interpretation of our estimated coefficients from Equation (2). Given that we are primarily interested in the effects of field day attendance, clicks on the personalized report, and their interaction on knowledge and recommended practice adoption, we also estimate the following model:

$$Y_{ic} = \alpha + \text{Attendance}_{ic}\beta_1 + \text{Report}_{ic}\beta_2 + [\text{Attendance}_{ic} \times \text{Report}_{ic}]\beta_3 + \gamma_c + \mathbf{X}_i'\boldsymbol{\delta} + \varepsilon_{ic}, \quad (3)$$

where Attendance_{ic} is an indicator for the event of farmer i's attending workshop c, Report_{ic} is an indicator for the event of the farmer's clicking on the personalized report corresponding to topic c, and the rest of the variables in the equation are as in Equation (2).

While we report the OLS parameter estimates for Equation (3), they are likely to be biased because farmers selected into treatment. For this reason, we also report the second-stage regression estimates from an instrumental variables (IV) strategy that instruments the indicator variables on the right-hand side of Equation (3) with the dummies on the right-hand side of Equation (2). Under the appropriate identification conditions as outlined in Imbens and Angrist (1994), the second-stage regression estimates from this IV strategy can be interpreted as average treatment effects for the group of so-called compliers.[6]

Throughout our exposition, the estimation sample includes only the 845 farmers who consented to participate in the study at baseline and reiterated their consent at endline. Table A.6 in Appendix A presents the correlation between a farmer consent dummy and treatment assignment dummies at baseline and endline. While assignment to the field days treatment is correlated with baseline consent by chance, we find no evidence of a significant correlation between endline consent and treatment assignment, indicating that differential attrition is not a concern in our estimation.

Table 3 presents our results. Column (1) reports the ITT effects of treatment assignment on knowledge index values. Assignment to the field days treatment increases knowledge by 2.7 percentage points (p=0.038), or 10 percent relative to the comparison group outcome. Similarly, assignment to the nudges treatment increases knowledge by 2.1 percentage points (p=0.075), or 7.8 percent relative to the comparison group estimate. The interaction of both treatments has a negative and statistically significant effect of 3.4 percentage points (p=0.049), indicating no complementarities in learning. However, the size of the interaction coefficient is not large enough for us to reject the null hypothesis of equality between the effect of field days and the combined effect of field days and nudges (p=0.303). Nor can we reject the null of equality be-

[6] We report the first-stage regression estimates for this IV strategy in Table A.7 of Appendix A.

tween the effect of nudges and the combined effect of nudges and field days (p=0.522).

In Table A.8 of Appendix A, we investigate the heterogeneity in the ITT effects of treatment assignment across groups of farmers defined by their baseline characteristics. The effects of both treatments are concentrated among young male farmers with high knowledge levels at baseline. Nonetheless, the field day effects are concentrated among farmers with incomplete primary schooling, while the nudge effects are concentrated among farmers with completed primary education.

Returning to Table 3, we report in Column (2) the OLS correlation of the knowledge index values at endline with the dummies for field day attendance and clicking on the personalized report, as well as their interaction. We report a statistically significant increase of 1 percentage point in knowledge from field day attendance (p=0.003) and an increase of 5.1 percentage points from clicking on the personalized report (p=0.004), whereas the coefficient for the interaction of both indicators is not statistically significant. However, as previously discussed, these estimates cannot be interpreted as causal because of selection bias.

Therefore, we report the second-stage regression estimates from our IV strategy in Column (3). Field day attendance has a marginally significant impact of 9 percentage points on knowledge index values (p=0.09), or 36 percent relative to the comparison group estimate. In contrast, we find no statistically significant impact of a respondent's clicking on her personalized report or the combination of field day attendance and clicking on the report.

In Table 4, we investigate the mechanisms driving the positive effect of field days on knowledge. As argued in the introduction, field days could increase farmers' digital engagement by educating them about mobile phone usage, reducing learning frictions, and establishing trust in digital advice. To test these potential mechanisms, we regress the farmers' responses to 4 yes/no questions about their perception of digitally transmitted advice on a dummy for assignment to the field days treatment. Assignment to the field days treatment increases the probability that a respondent reports having received automated messaging campaigns by 9.7 percentage points (p=0.001), being able to open campaign messages by 8.6 percentage points (p=0.004), trusting the automated campaign messages by 7.8 percentage points (p=0.016), and understanding how to apply digital advice by 8.2 percentage points (p=0.012).

Turning to the results on the adoption of recommended practices back in Table 3, we report no significant ITT effects in Column (4) for either treatment or their combination. We report significant correlations only between field day attendance and knowledge and between clicking on nudges and knowledge, in Column (5). However, these correlations do not reflect causal relationships for the reasons outlined above. Furthermore, we do not find significant ITT effect estimates for the adoption of the fertilization recommendations contained in the personalized reports, as shown in Table A.9 of Appendix A.

9 Impacts on Productivity, Palm Area, and Conservation

We finish our analysis by testing the effects of field days and nudges on self-reported plot-level productivity measures, including palm harvest, sales price, number of harvest days, production costs in the first quarter of 2024, and palm area calculated from satellite imagery. Since the values of these outcome variables vary widely with plot size, we follow McKenzie (2012) and estimate the following analysis of covariance (ANCOVA) specification for the ITT effect of our experimental treatments on the outcome Y_{i1} of plot i at endline to gain power in estimation:

$$Y_{i1} = \alpha + T1_i\beta_1 + T2_i\beta_2 + [T1_i \times T2_i]\beta_3 + \mathbf{X}_i'\boldsymbol{\gamma} + Y_{i0}\lambda + \varepsilon_i, \tag{4}$$

where Y_{i0} is the pre-treatment outcome and the rest of the variables are defined as in Equation (2). Standard errors are robust to heteroskedasticity of unknown form. As in previous sections, we also report IV regression results when our ITT estimates indicate an effect of assignment on the outcomes of interest.

Table A.10 in Appendix A shows no statistically significant evidence of an effect of treatment assignment on any of our self-reported measures of productivity or production costs. However, our analysis of the impacts on the plot share of palm area in Table 5 reveals positive impacts of assignment to the field days treatment on the palm share. We begin with the ITT effect estimates in Panel A: Column (1) shows that assignment to the field days treatment increased palm area by 3.8 percentage points (p=0.014), or 0.9 hectares. When we decompose the palm area of each plot into the land conservation categories defined in ProAmazonia's 2018 HCV map of the region in Columns (2) through (4), we find that the increases occurred in LCV areas. Furthermore, when we decompose the palm area into health categories elaborated by means of NDVI values in Columns (5) through (7), we find that the increase reflects an expansion of mid-health palm area. These findings are corroborated in Panels B and C, which report OLS and IV impact estimates, respectively. Attendance of all the field days results in a marginally significant increase in palm land area of 12 percentage points (p=0.066), or 2.82 hectares.

10 Conclusion

This paper studied the complementarity in the effects of in-person field days and behavioral nudges on engagement with digitally provided information, farmer knowledge, recommended practice adoption, productivity, and environmental conservation in the context of oil palm agriculture in the Ecuadorian Amazon. We find that field days positively impact farmers' engagement with automated messaging campaigns and knowledge by reducing digital illiteracy and

other learning frictions and improving trust. We also find that field days expand palm plantations in low-conservation-value areas within the farmers' plots, implying that training is an effective policy for reducing the tensions between the development goals of sustainability and poverty reduction. In line with previous literature, we find no impacts on adoption of recommended practices or productivity. Finally, nudges proved successful in inducing engagement with personalized farmer reports, implying that nudge interventions could potentially succeed in highlighting other types of digital content.

Another key implication of our findings is that a cost-effectiveness comparison of in-person agricultural extension and digital information provision as substitutes could yield misleading policy advice because some learning goals may be accomplished only through in-person immersive learning and others only through digital information provision. Future research should instead focus on identifying the type of hybrid training that could have the most transformative impacts on the adoption of sustainable agricultural practices.

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Tables

Table 1: Intention-to-Treat Effects of Treatment on Digital Engagement

Regressor	Nursery	Pollination	Fertilization	IPM	All
	(1)	(2)	(3)	(4)	(5)
			Panel A. Reading Rates		
Field Days	0.085**	0.083**	0.078**	0.088**	0.083***
	(0.036)	(0.036)	(0.036)	(0.037)	(0.032)
Nudges	0.018	-0.019	0.002	0.002	0.004
	(0.035)	(0.037)	(0.036)	(0.036)	(0.032)
Field Days × Nudges	0.005	0.031	0.021	0.036	0.022
	(0.050)	(0.052)	(0.052)	(0.053)	(0.046)
Comparison	0.636***	0.630***	0.623***	0.581***	0.617***
	(0.025)	(0.025)	(0.025)	(0.025)	(0.023)
N	7,496	3,748	7,496	6,559	25,299
Farmers	937	937	937	937	937
Messages	8	4	8	7	27
R-Squared	.237	.23	.233	.243	.231
			Panel B. Response Rates		
Field Days	0.054**	0.011	0.045***	0.053***	0.045***
	(0.024)	(0.017)	(0.015)	(0.018)	(0.014)
Nudges	0.024	0.004	0.022	0.016	0.017
	(0.022)	(0.016)	(0.013)	(0.016)	(0.013)
Field Days × Nudges	-0.038	-0.003	-0.034	-0.018	-0.024
	(0.034)	(0.024)	(0.022)	(0.026)	(0.021)
Comparison	0.076***	0.049***	0.032***	0.057***	0.050***
	(0.014)	(0.011)	(0.009)	(0.010)	(0.009)
N	1,874	1,874	4,685	6,559	14,992
Farmers	937	937	937	937	937
Interaction Opportunities	2	2	5	7	16
R-Squared	.040	.041	.028	.034	.027
			Panel B. Link-Clicking Rates		
Field Days	0.047*	0.008	0.019*	0.008	0.014
	(0.028)	(0.013)	(0.010)	(0.009)	(0.008)
Nudges	0.013	-0.004	0.009	0.004	0.004
	(0.025)	(0.012)	(0.009)	(0.010)	(0.008)
Field Days × Nudges	-0.047	0.024	0.001	0.012	0.007
	(0.038)	(0.020)	(0.016)	(0.015)	(0.013)
Comparison	0.074***	0.033***	0.017***	0.023***	0.027***
	(0.017)	(0.009)	(0.006)	(0.006)	(0.005)
N	937	2,811	3,748	5,622	13,118
Farmers	937	937	937	937	937
Interaction Opportunities	1	3	4	6	14
R-Squared	.034	.026	.025	.02	.017

Notes: This table shows the intention-to-treat effect in percentage points of the specified interventions on message reading, response, and link-clicking rates. The estimation samples in Columns (1) through (4) include only farmers who received messages with clickable links or interactive response options for the specified campaign, whereas the estimation sample in Column (5) pools farmers who received automated campaign messages with clickable links or interactive response options in any of the campaigns. "IPM" stands for integrated pest management. The estimates for "Link-Clicking Rates" exclude clicks on the links to the personalized reports included in the nudges treatment. The "Comparison" coefficient is the outcome mean for the reference group in the regression. All regressions control for strata dummies. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the farmer level. * $p < 0 - .1$, ** $p < 0.05$, *** $p < 0.01$.
Sources: Authors' elaboration from data from the mobile platform log file.

Table 2: Intention-to-Treat Effects on Personalized Report Click Rates

Regressor	Pollination	Fertilization	IPM	All
	(1)	(2)	(3)	(4)
Field Days	-0.003	0.001	-0.002	-0.001
	(0.020)	(0.014)	(0.016)	(0.010)
Nudges	0.119***	0.077***	0.048**	0.081***
	(0.028)	(0.021)	(0.020)	(0.014)
Field Days × Nudges	0.053	0.005	0.026	0.028
	(0.042)	(0.031)	(0.031)	(0.020)
Comparison	0.048***	0.022**	0.032***	0.034***
	(0.014)	(0.010)	(0.011)	(0.007)
N	937	937	937	2,811
Farmers	937	937	937	937
R-Squared	.09	.085	.064	.065

Notes: This table shows the intention-to-treat effect in percentage points of the specified interventions on the click rates for the links to the personalized reports. The estimation samples in Columns (1) through (3) include only the farmers who received campaign-specific personalized reports, whereas the estimation sample in Column (5) pools all farmers who received reports in any of the campaigns. “IPM" stands for integrated pest management. The “Comparison” coefficient is the outcome mean for the reference group in the regression. All regressions control for strata dummies. Standard errors are robust to heteroskedasticity of unknown form. ** $p < 0.05$, *** $p < 0.01$.
Sources: Authors’ elaboration from data from the mobile platform log file.

Table 3: Effects on Knowledge and Practice Adoption

	Knowledge			Recommended Practices		
Regressor	ITT	OLS	IV	ITT	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Field Days	0.027**			-0.016		
	(0.013)			(0.019)		
Nudges	0.021*			0.003		
	(0.012)			(0.019)		
Field Days × Nudges	-0.034**			0.027		
	(0.017)			(0.027)		
Attendance		0.010***	0.090*		0.020***	-0.057
		(0.003)	(0.050)		(0.006)	(0.065)
Click on Personalized Report		0.051***	0.269		0.085***	0.023
		(0.018)	(0.172)		(0.030)	(0.250)
Interaction		-0.012	-0.405		-0.014	0.265
		(0.010)	(0.253)		(0.015)	(0.332)
Comparison	0.273***	0.282***	0.250***	0.463***	0.453***	0.472***
	(0.020)	(0.018)	(0.029)	(0.032)	(0.030)	(0.043)
N	2,535	2,535	2,535	2,535	2,535	2,535
p-value for:						
Field Days=Both	.303			.127		
Nudges=Both	.522			.577		
Farmers	845	845	845	845	845	845
Exam Topics	3	3	3	3	3	3
R-Squared	.183	.187	-	.277	.283	-

Notes: This table shows intention-to-treat (ITT), ordinary least squares (OLS), and instrumental variable (IV) estimates of the effects of the specified interventions on farmers' knowledge and adoption of recommended agricultural practices in percentage points. The knowledge test scores are the shares of correct answers in the standardized test for each topic, and the recommended practices indices are the shares of recommended practices that farmers adopted. The estimation sample includes farmers who answered the endline survey. The "Comparison" coefficient is the outcome mean for the reference group in the regression. All regressions control for strata and campaign topic dummies. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the farmer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Sources: Authors' elaboration from data from the log file of the mobile platform and the experimental baseline and endline surveys.

Table 4: Mechanisms Underlying the Effects of Field Days on Digital Engagement

Regressor	Receives Automated Campaigns	Is Able to Open Campaign Messages	Trusts Automated Campaign Messages	Understands How to Apply Advice
	(1)	(2)	(3)	(4)
Field Days	0.097***	0.086***	0.078**	0.082**
	(0.030)	(0.030)	(0.032)	(0.033)
Comparison	0.564***	0.569***	0.464***	0.506***
	(0.074)	(0.074)	(0.076)	(0.075)
Farmers	845	845	845	845
R-Squared	.126	.132	.118	.11

Notes: This table presents results on the roles of the specified mechanisms in driving the effect of field day attendance on farmers' digital engagement. The estimation sample in each column includes farmers who answered the respective survey question at endline. Standard errors are robust to heteroskedasticity of unknown form. For each column, the "Comparison" coefficient is the outcome mean for the reference group in the regression. All regressions control for strata dummies. ** $p < 0.05$, *** $p < 0.01$.
Sources: Authors' elaboration from data from the the experimental endline survey.

Table 5: Effects on Plot Share of Oil Palm

Regressor	Total	By Conservation Value			By Health Category		
		Low	Medium	High	Low	Medium	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A. ITT			
Field Days	0.038**	0.059***	-0.017	-0.005	0.006	0.038*	-0.001
	(0.015)	(0.023)	(0.014)	(0.008)	(0.006)	(0.019)	(0.018)
Nudges	0.026*	0.025	-0.002	0.002	-0.001	0.034*	-0.002
	(0.014)	(0.023)	(0.014)	(0.008)	(0.004)	(0.018)	(0.018)
Field Days × Nudges	-0.020	-0.040	0.027	-0.007	-0.005	-0.017	-0.008
	(0.022)	(0.032)	(0.021)	(0.011)	(0.007)	(0.028)	(0.026)
R-Squared	.774	.565	.131	.128	.057	.395	.366
				Panel B. OLS			
Attendance Rate	0.018**	0.028**	-0.006	-0.003	0.002	0.016	-0.000
	(0.009)	(0.012)	(0.007)	(0.006)	(0.003)	(0.010)	(0.009)
Report Click Rate	-0.001	-0.015	0.026	-0.012	-0.011	-0.005	0.017
	(0.024)	(0.045)	(0.030)	(0.014)	(0.007)	(0.043)	(0.044)
Interaction	-0.003	0.009	-0.006	-0.006	-0.006	0.015	-0.015
	(0.024)	(0.034)	(0.021)	(0.012)	(0.006)	(0.030)	(0.028)
R-Squared	.773	.565	.13	.128	.057	.392	.366
				Panel C. IV			
Attendance Rate	0.120*	0.194*	-0.072	-0.001	0.018	0.119	0.007
	(0.066)	(0.101)	(0.060)	(0.031)	(0.022)	(0.082)	(0.072)
Report Click Rate	0.260	0.259	-0.036	0.037	-0.017	0.346	-0.014
	(0.179)	(0.274)	(0.165)	(0.090)	(0.047)	(0.227)	(0.198)
Interaction	-0.330	-0.584	0.341	-0.087	-0.053	-0.318	-0.091
	(0.322)	(0.490)	(0.303)	(0.150)	(0.093)	(0.408)	(0.350)
R-Squared	.723	.447	-.0642	.0905	.00871	.288	.358
N	946	946	946	946	946	946	946
Farmers	845	845	845	845	845	845	845
Plots	946	946	946	946	946	946	946

Notes: This table presents estimates of the effects of the specified interventions on share of farmers' plots dedicated to oil palm cultivation. The outcome variable in Column (1) is the share of the plot area covered by oil palm plantations. Conservation value categories are formulated on the basis of the Inter-American Development Bank's 2018 map. The outcome variables in Columns (2) through (4) are the shares of the plot area covered by palm plantations intersecting low-, medium-, and and high-conservation-value areas in the plot, respectively. Health categories are calculated on the basis of the normalized difference vegetation index for the palm area of each plot. The outcome variables in Columns (5) through (7) are the shares of the plot area covered by palm plantations of low, medium, and high health, respectively. The estimation sample includes the plots of the farmers who consented to answer the endline survey. The "Comparison" coefficient is the outcome mean for the reference group in the regression. All regressions control for strata dummies. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the farmer level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Sources: Authors' elaboration from satellite imagery and the experimental endline survey.

Supplementary Appendix: For Online Publication Only

This appendix contains additional information and analyses. Appendix A presents additional figures and tables. Documentary evidence of the field experiment activities is shown in Appendix B.

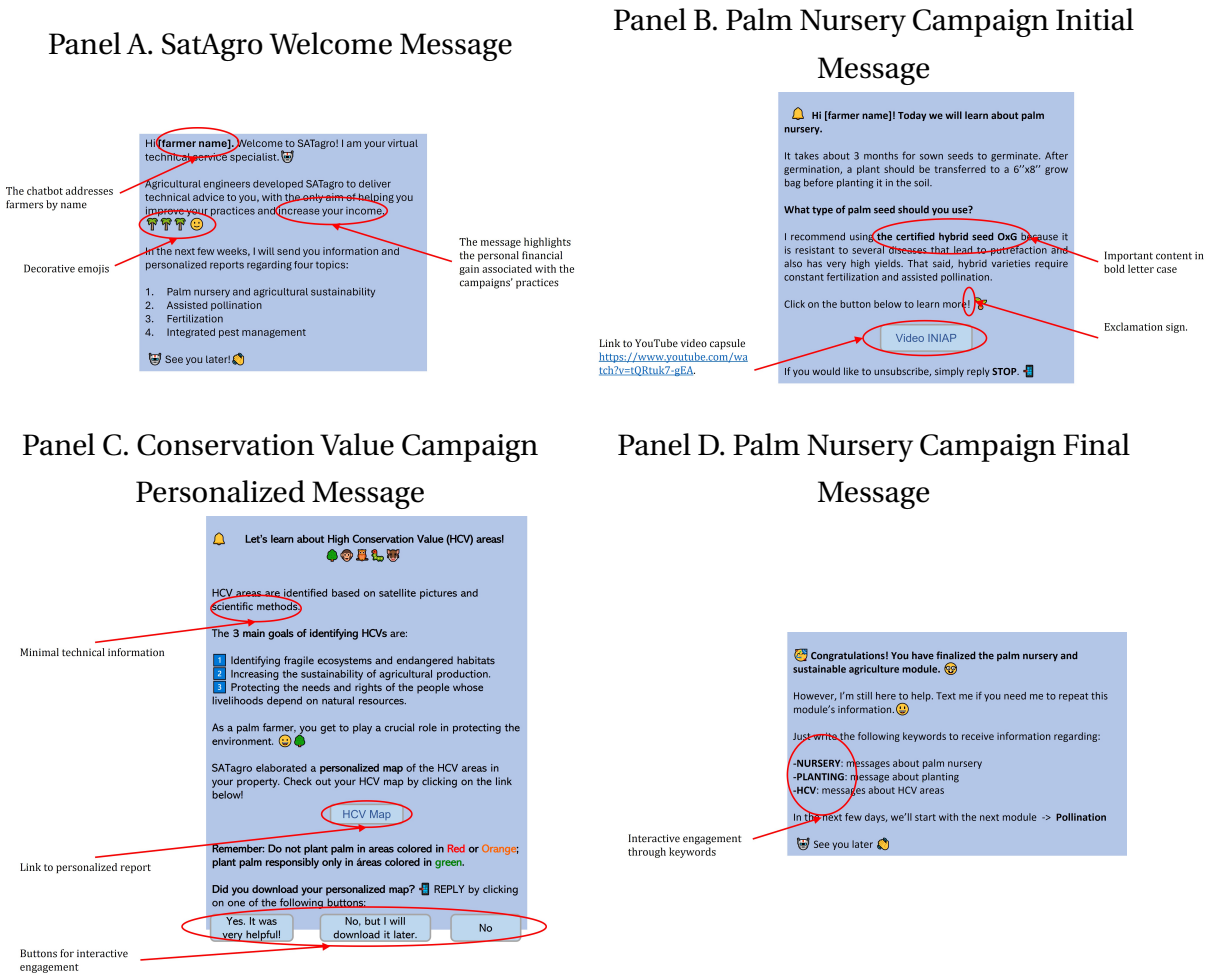
A Additional Figures and Tables

Figure A.1: Study Location



Notes: This figure depicts the study location within the provinces of Orellana and Sucumbíos in the northeast of Ecuador. Polygons represent the plots of the farmers participating in the field experiment.
Sources: Authors' elaboration from satellite imagery and data from the baseline agricultural census.

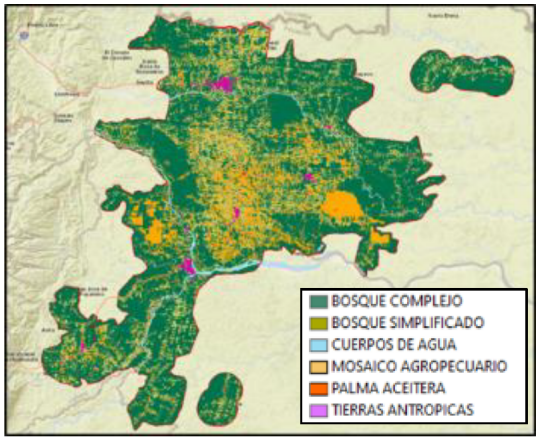
Figure A.2: Crafting of Text Messages on the Basis of Behavioral Economics Insights



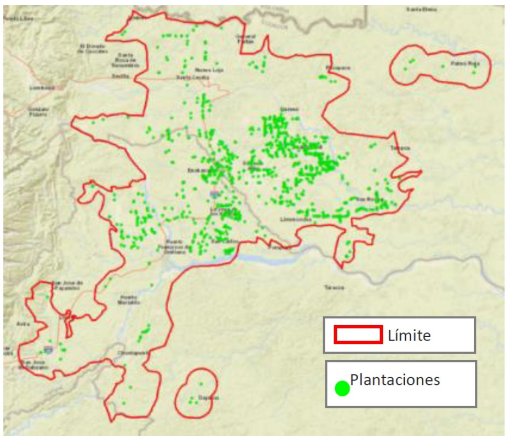
Notes: This figure presents examples of SatAgro's messaging campaigns, crafted on the basis of insights from the behavioral economics literature. Panel A reproduces SatAgro's welcome message, while Panels B through D reproduce selected text messages from the palm nursery and environmental conservation campaigns. Panel A shows how the messages directly addressed farmers by name, used decorative emojis, and appealed to the financial benefits of the information in the campaigns. Panel B illustrates the usage of bold font to highlight important content, exclamation signs in motivational phrases, and buttons linked to external content. Panel C illustrates the usage of heuristics instead of technical information, buttons linked to the personalized reports, and buttons for two-way interactive engagement. Finally, Panel D illustrates the usage of keywords to maximize interactive engagement.
Sources: Authors' transcription of SatAgro chatbot messages.

Figure A.3: Production of Personalized PDF Reports for Farmers

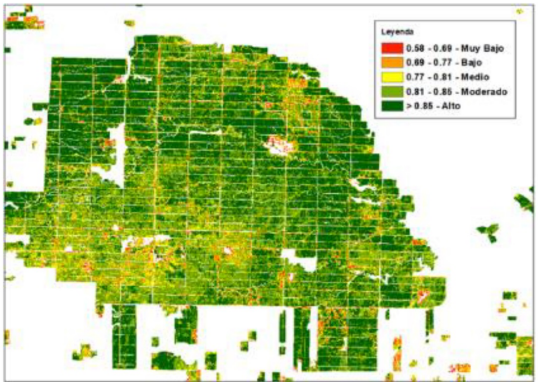
Panel A. Classification Algorithm



Panel B. Palm Plantations



Panel C. Plot-Level Palm Area Map



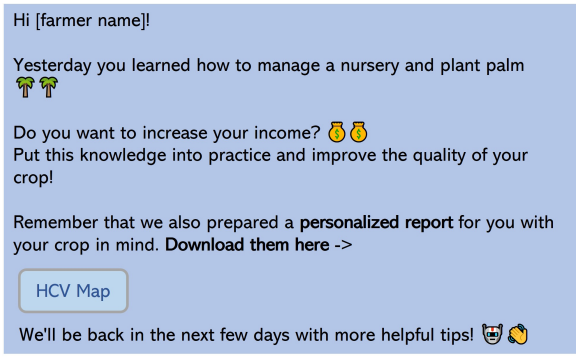
Panel D. Tabular Scale Descriptor

Level	Description
Very Low	Plants with very low vigor, showing minimal chlorophyll and photosynthesis. The plant is severely and progressively affected, potentially leading to irreversible damage or death.
Low	Plants with low vigor, showing reduced chlorophyll and photosynthesis. They are highly susceptible to pests and diseases, experiencing significant physiological stress.
Medium	Plants with medium vigor, moderately susceptible to pests and diseases. They have average chlorophyll and photosynthesis levels, which can moderately impact productivity.
Moderate	Plants with moderate vigor, slightly susceptible to pests and diseases. They have moderate NDVI values, indicating chlorophyll and photosynthesis levels that may affect production potential.
High	Plants with high vigor, less prone to pests and diseases. They have higher NDVI values, indicating good health and high production potential.

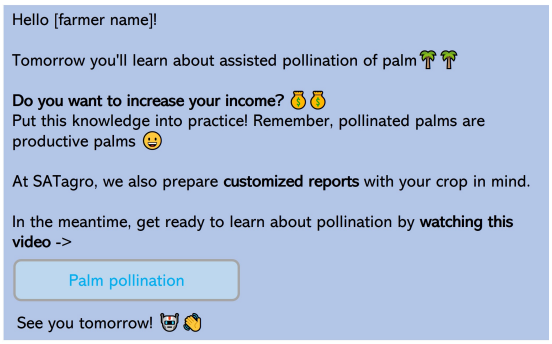
Notes: This figure illustrates the procedure followed to produce the personalized PDF reports for farmers. Panel A shows the end product of our classification algorithm, with the identified palm areas colored in red. Panel B shows the locations of the identified palm plantations. Panel C exemplifies the information on the palm area in each individual plot extracted on the basis of customary vegetation indexes and included in the farmer's plot health report. Finally, Panel D exemplifies the construction of tabular scale descriptors to facilitate farmers' understanding of the information in the personalized report.
Sources: Authors' elaboration from satellite imagery, object classification algorithms, and customary vegetation indexes.

Figure A.4: Behavioral Nudges

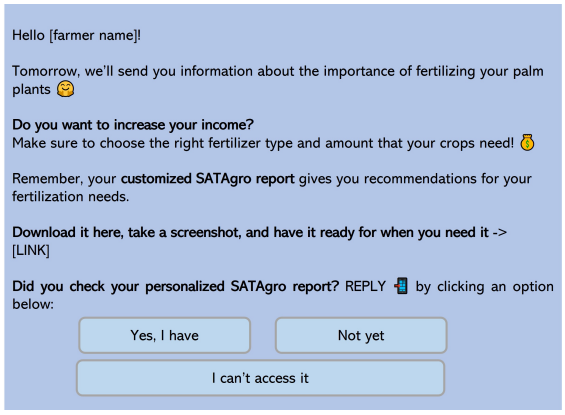
Panel A. Palm Nursery Campaign



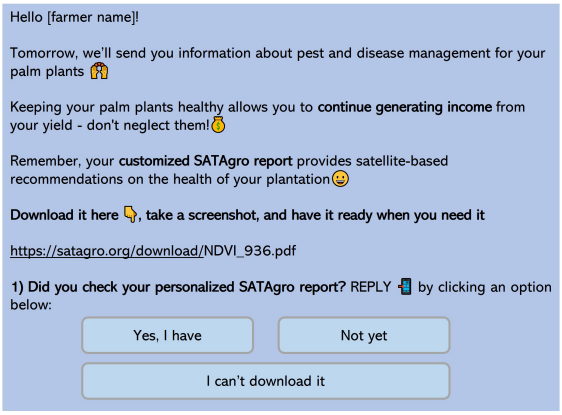
Panel B. Assisted Pollination Campaign



Panel C. Fertilization Campaign

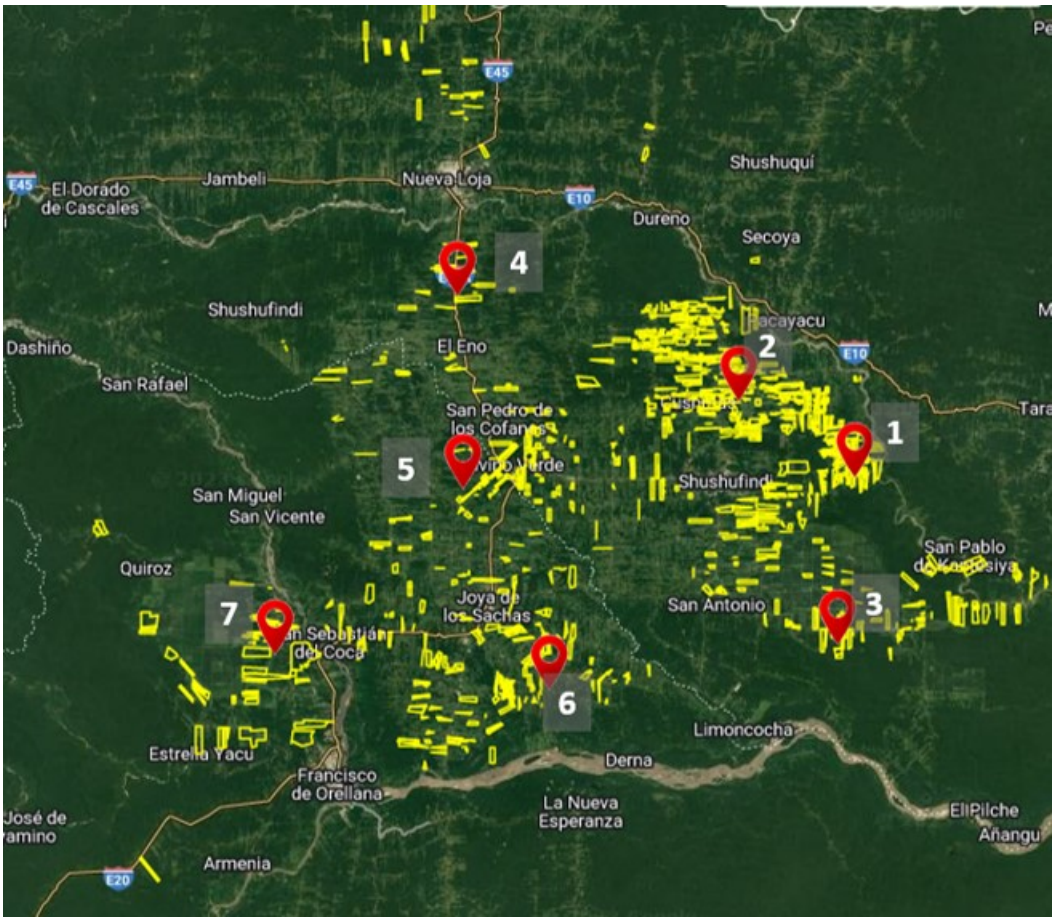


Panel D. Integrated Pest Management Campaign



Notes: This figure reproduces the behavioral nudges corresponding to each of the 4 SatAgro messaging campaigns. Except in the first messaging campaign, the behavioral nudges were sent to recipients in anticipation of the regular messaging campaign messages. The first nudge was sent *after* the message from regular campaign on palm nursery and sustainable agriculture to ensure that the farmers did not receive a text message before they had become familiar with SatAgro.
Source: Authors' transcription of SatAgro behavioral nudges.

Figure A.5: Training Venues



Notes: This figure presents the location of the 7 venues for the field days treatment. Polygons represent the locations of the plots owned by the farmers participating in the field experiment.
Sources: Authors' elaboration from satellite imagery and data from the baseline agricultural census.

Table A.1: Sample Representativeness

	Pr(Participant)		Explanatory Variable	
	Coefficient	Std. Error	Mean	Std. Deviation
	(1)	(2)	(3)	(4)
Age	.013	.011	50.5	14
Smartphone Ownership	.464	.556	.928	.258
Distance to Nearest Venue	-.01	.011	7.5	11.1
χ^2-statistic for joint test	2.913			
p-value	.405			
N	990			

Notes: This table shows the coefficients from a logit regression of an indicator for participation in the field experiment on farmer age, smartphone ownership, and distance to the nearest venue for field days.
Sources: Authors' elaboration from data from the agricultural census of May 2023 and the baseline survey of June 2023.

Table A.2: Stratification Groups

Nearest Venue	Plot Size	Test Messages	Percent
(1)	(2)	(3)	(4)
1	≤ Median	Not read	5.2
1	>Median	Not read	3.6
1	≤ Median	Read	9.5
1	>Median	Read	4.0
2	≤ Median	Not read	5.8
2	>Median	Not read	4.8
2	≤ Median	Read	9.6
2	>Median	Read	6.1
3	≤ Median	Not read	2.8
3	>Median	Not read	3.2
3	≤ Median	Read	1.6
3	>Median	Read	4.3
4	≤ Median	Not read	0.6
4	>Median	Not read	1.9
4	≤ Median	Read	0.6
4	>Median	Read	2.1
5	≤ Median	Not read	3.7
5	>Median	Not read	4.4
5	≤ Median	Read	4.9
5	>Median	Read	3.8
6	≤ Median	Not read	2.0
6	>Median	Not read	2.0
6	≤ Median	Read	2.2
6	>Median	Read	4.4
7	≤ Median	Not read	0.4
7	>Median	Not read	1.8
7	≤ Median	Read	1.0
7	>Median	Read	3.4

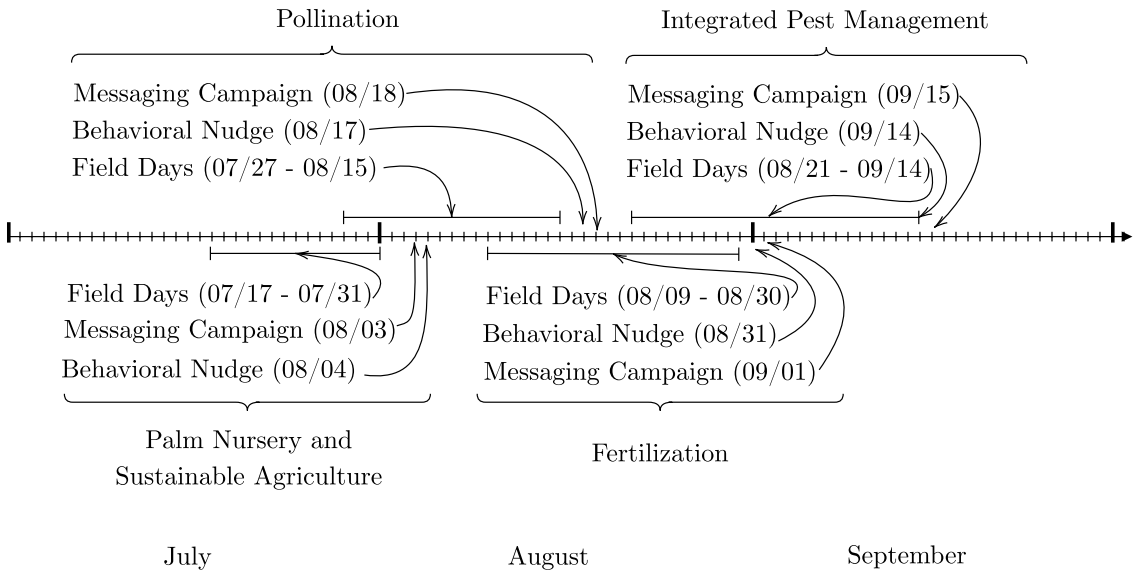
Notes: This table shows the randomization strata for the experiment. There is one observation per palm farmer. The numbers in Column (1) correspond to the locations of the venues for the field days. The plot size categories in Column (2) are relative to the cross-sectional distribution of the size of the largest plot owned at the farmer level in May 2023. Column (3) presents the test message reading status.
Sources: Authors' elaboration from data from the agricultural census of May 2023 and SatAgro log file.

Table A.3: Field Days Calendar

Date	Engineer 1		Engineer 2	Engineer 3			
	Location 1	Location 2	Location 3	Location 4	Location 5	Location 6	Location 7
7/17/2023	Nursery			Nursery			
7/18/2023	Nursery				Nursery		
7/19/2023	Nursery				Nursery		
7/20/2023	Nursery						
7/21/2023						Nursery	
7/24/2023		Nursery	Nursery			Nursery	
7/25/2023		Nursery					Nursery
7/26/2023		Nursery					Nursery
7/27/2023		Nursery		Pollination			
7/31/2023		Nursery	Nursery		Pollination		
8/1/2023	Pollination				Pollination		
8/2/2023	Pollination					Pollination	
8/3/2023	Pollination					Pollination	
8/7/2023	Pollination		Pollination				Pollination
8/8/2023		Pollination					Pollination
8/9/2023		Pollination		Fertilization			
8/10/2023		Pollination			Fertilization		
8/11/2023					Fertilization		
8/14/2023		Pollination	Pollination			Fertilization	
8/15/2023		Pollination				Fertilization	
8/16/2023	Fertilization						Fertilization
8/17/2023	Fertilization						Fertilization
8/21/2023	Fertilization		Fertilization	IPM			
8/22/2023	Fertilization				IPM		
8/23/2023		Fertilization			IPM		
8/24/2023		Fertilization				IPM	
8/28/2023		Fertilization	Fertilization			IPM	
8/29/2023		Fertilization					IPM
8/30/2023		Fertilization					IPM
8/31/2023	IPM						
9/4/2023	IPM		IPM				
9/5/2023	IPM						
9/6/2023	IPM						
9/7/2023		IPM					
9/11/2023		IPM	IPM				
9/12/2023		IPM					
9/13/2023		IPM					
9/14/2023		IPM					

Note: This table shows the workshop calendar by engineer, venue assignment, and date. There were 18 workshops for each of the following field day topics: palm nursery and sustainable agriculture ("nursery"), pollination, fertilization, and integrated pest management ("IPM"). Each workshop involved a different group of 25 farmers or fewer. The farmers were assigned to their closest training location as measured by road distance and, within a venue, were randomly assigned to a preset series of training dates based on engineer availability.
Sources: Authors' elaboration from engineers' calendar availability and venue assignment.

Figure A.6: Experiment Timeline



Notes: This figure depicts the implementation timeline for the messaging campaigns and the field days and behavioral nudges treatments.
Sources: Authors' elaboration.

Table A.4: Balance of Key Variables Prior to Treatment

	Control	Field Days	Nudges	Field Days & Nudges	p-value
	(1)	(2)	(3)	(4)	(5)
			Panel A. Farmers		
Age	45.0	48.0	46.1	47.1	0.2
	(1.3)	(1.1)	(1.0)	(1.1)	
Female (%)	19.9	20.3	23.0	24.2	0.6
	(2.5)	(2.7)	(2.7)	(2.9)	
Read Initial Test Message (%)	57.0	58.1	58.4	57.4	1.0
	(3.1)	(3.3)	(3.2)	(3.3)	
Farmers	251	227	243	223	
			Panel B. Plots		
Land Area (Ha)	29.7	28.1	28.9	27.2	0.9
	(2.1)	(3.4)	(1.8)	(2.0)	
Palm Area (Ha)	14.4	13.8	15.4	13.5	0.5
	(1.3)	(1.0)	(0.8)	(0.8)	
Plots	279	254	290	250	

Notes: This table shows evidence of balance on the mean values of key variables across the experimental groups prior to treatment. Standard errors are in parentheses. The p-value in Column (5) corresponds to a test of equality in means between the three treatment groups and the control group.
Sources: Authors' elaboration from data from the agricultural census.

Table A.5: Field Day Attendance Rates by Treatment Group

Regressor	Nursery	Pollination	Fertilization	IPM	All
	(1)	(2)	(3)	(4)	(5)
Field Days	0.186***	0.446***	0.540***	0.729***	0.475***
	(0.030)	(0.066)	(0.089)	(0.122)	(0.042)
Nudges	0.029	0.043	0.062	0.053	0.047*
	(0.021)	(0.045)	(0.057)	(0.080)	(0.027)
Field Days & Nudges	0.204***	0.509***	0.658***	0.834***	0.551***
	(0.031)	(0.068)	(0.092)	(0.125)	(0.044)
Comparison	0.037***	0.107***	0.102***	0.165***	0.103***
	(0.012)	(0.029)	(0.035)	(0.052)	(0.017)
N	944	944	944	944	3,776
R-Squared	.106	.117	.116	.114	.0876

Notes: This table shows the impact of treatment assignment on field day attendance rates in percentage points. The outcome variable is a field day attendance dummy at the lot level. “IPM" stands for integrated pest management. The “Comparison” coefficient is the attendance rate for the reference group in the regression, whereas the other coefficients show the attendance rates for the each of the treatment groups. All regressions control for strata dummies. Standard errors are robust to heteroskedasticity of unknown form. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Sources: Authors’ elaboration from data from the mobile platform log file.

Table A.6: Treatment Assignment and Farmer Consent at Baseline and Endline

Regressor	Baseline	Endline
	(1)	(2)
Field Days	-0.054**	-0.011
	(0.024)	(0.020)
Nudges	-0.026	0.002
	(0.022)	(0.017)
Field Days & Nudges	-0.015	0.014
	(0.021)	(0.016)
Comparison	0.952***	0.962***
	(0.013)	(0.012)
Farmers	944	877
p-value for Joint Significance Test	.16	.575
R-Squared	.006	.002

Notes: This table shows the correlation of treatment assignment with a dummy for farmer consent to participate in the baseline and endline surveys. The estimation sample includes all randomized farmers in Column (1) and only the farmers who consented at baseline in Column (2). In each column, the “Comparison” coefficient estimate is the mean consent rate for the control group, whereas the other coefficient estimates are differences from the control group outcome. Standard errors are robust to heteroskedasticity of unknown form. ** $p < 0.05$, *** $p < 0.01$.
Sources: Authors’ elaboration from data from the experimental baseline and endline surveys.

Table A.7: First-Stage Regression Results for Knowledge and Practice Adoption

Regressor	Attendance	Download	Interaction
	(1)	(2)	(3)
Field Days	0.607***	0.002	0.071**
	(0.087)	(0.013)	(0.028)
Nudges	0.063	0.085***	0.019
	(0.058)	(0.019)	(0.018)
Field Days × Nudges	0.034	0.021	0.106**
	(0.129)	(0.027)	(0.050)
N	2,535	2,535	2,535
F-Statistic of Excluded Instruments	33	17.1	9.5
Farmers	845	845	845
Exam Topics	3	3	3
R-Squared	.114	.08	.042

Notes: The estimation sample includes farmers who answered the endline survey. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the farmer level. All regressions control for strata and campaign topic dummies. ** $p < 0.05$, *** $p < 0.01$.
Sources: Authors' elaboration from data from the experimental endline survey.

Table A.8: Heterogeneity in Knowledge Effects Across Selected Dichotomous Characteristics

	Knowledge Higher than Median	Younger than Median	Male	Completed Primary Education
	(1)	(2)	(3)	(4)
Field Days × No	0.015	0.017	0.016	0.030*
	(0.018)	(0.017)	(0.031)	(0.018)
Field Days × Yes	0.045**	0.039**	0.028**	0.027
	(0.018)	(0.019)	(0.014)	(0.019)
Nudges × No	-0.001	-0.002	0.006	-0.003
	(0.017)	(0.016)	(0.024)	(0.018)
Nudges × Yes	0.039**	0.038**	0.028**	0.038**
	(0.015)	(0.017)	(0.013)	(0.016)
Field Days × Nudges × No	-0.022	-0.015	0.007	-0.017
	(0.024)	(0.025)	(0.039)	(0.025)
Field Days × Nudges × Yes	-0.052**	-0.051**	-0.046**	-0.050**
	(0.023)	(0.025)	(0.019)	(0.025)
N	2,535	2,535	2,535	2,535
p-value for:				
Field Days × No = Both × No	.183	.353	.683	.269
Nudges × No = Both × No	.655	.93	.333	.45
Field Days × Yes = Both × Yes	.466	.471	.192	.514
Nudges × Yes = Both × Yes	.666	.426	.195	.148
Farmers	845	845	845	845
Exam Topics	3	3	3	3
R-Squared	.21	.188	.187	.198

Notes: The estimation sample in each column includes farmers who self-reported their values on the partitioning characteristic at baseline. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the farmer level. All regressions control for strata and campaign topic dummies. * $p < 0.1$, ** $p < 0.05$.
Sources: Authors' elaboration from data from the log file of the mobile platform and the experimental baseline and endline surveys.

Table A.9: Effects on Adoption of Personalized Fertilizer Recommendations

Regressor	ITT	OLS	IV
	(1)	(2)	(3)
Field Days	-0.657		
	(0.818)		
Nudges	-0.635		
	(0.846)		
Field Days × Nudges	0.416		
	(0.807)		
Field Day Attendance Rate		-0.229	-2.3
		(0.164)	(3.2)
Report Click Rate		-0.065	-6.7
		(0.213)	(9.3)
Interaction		0.144	7.2
		(0.223)	(12.7)
Comparison	1.120*	0.671***	1.4
	(0.595)	(0.062)	(1.2)
N	946	946	946
Field Days=Both	.337		
Nudges=Both	.224		
Farmers	845	845	845
R-Squared	.037	.035	-

Notes: This table shows intention-to-treat (ITT), ordinary least squares (OLS), and instrumental variable (IV) estimates of the effects of the specified interventions on farmers' adoption of recommended fertilizer practices in percentage points. The outcome variable is the absolute difference between the recommended fertilizer amount in kilograms per plant and the actual usage of fertilizer by the farmer at endline, normalized by the recommended value. The estimation sample includes farmers who answered the endline survey. The "Comparison" coefficient is the outcome mean for the reference group in the regression. All regressions control for strata dummies. Standard errors are robust to heteroskedasticity of unknown form. * $p < 0.1$, *** $p < 0.01$.
Sources: Authors' elaboration from data from the personalized fertilization reports and the experimental endline surveys.

Table A.10: Intention-to-Treat Effects on Self-Reported Productivity and Production Costs

Regressor	Harvest (Tons)	Price p/Ton	Harvest Days	Production Costs (USD)			
				Total	Fertilizer	Pesticide	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Field Days	-0.0	0.1	0.1	459.0	289.8	60.5	191.1
	(3.3)	(3.9)	(0.5)	(941.4)	(244.9)	(71.6)	(629.2)
Nudges	2.1	3.5	0.5	-229.8	28.5	-5.7	-151.1
	(3.9)	(3.5)	(0.5)	(759.7)	(171.3)	(71.1)	(560.4)
Field Days × Nudges	-1.8	0.1	-0.5	-111.2	80.1	32.8	-376.6
	(5.1)	(5.1)	(0.7)	(1247.6)	(446.3)	(112.0)	(816.7)
Comparison	24.6***	144.7***	17.8***	6829.5***	1380.8***	576.0***	3900.8***
	(2.0)	(2.7)	(0.4)	(502.3)	(101.4)	(45.6)	(346.5)
N	946	946	946	946	946	946	946
Farmers	845	845	845	845	845	845	845
Plots	946	946	946	946	946	946	946
R-Squared	.0005	.002	.002	.0007	.003	.002	.0009

Notes: This table shows the impact of treatment assignment on productivity and production costs at the plot level. All amounts correspond to quarterly totals from January to March 2024. The estimation sample includes all plots for which farmers reported information in the endline survey. The "Comparison" coefficient is the average for the control group, whereas the other coefficients show the effects for the treatment groups. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the farmer level. *** $p < 0.01$.
Sources: Authors' elaboration from data from the experimental baseline and endline surveys.

Table A.11: First-Stage Regression Results for Plot Share of Palm Oil

Regressor	Attendance	Download	Interaction
	(1)	(2)	(3)
Field Days	0.455***	-0.004	0.047**
	(0.067)	(0.014)	(0.020)
Nudges	0.042	0.095***	0.013
	(0.042)	(0.023)	(0.012)
Field Days × Nudges	0.040	0.023	0.091**
	(0.099)	(0.031)	(0.037)
N	946	946	946
F-Statistic of Excluded Instruments	32.5	16.4	10.3
Farmers	845	845	845
Plots	946	946	946
R-Squared	.137	.143	.078

Notes: The estimation sample includes the plots of farmers who consented to answer the endline survey. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the farmer level. All regressions control for strata dummies. ** $p < 0.05$, *** $p < 0.01$.
Sources: Authors' elaboration from data from the experimental endline survey.

B Documentary Evidence

Figure B.1: Personalized PDF Reports

Panel A. High-Conservation-Value Areas Report



Panel B. Fertilization Report



Notes: This figure presents documentary evidence of the SatAgro personalized PDF reports, as downloaded by local farmers in the Orellana and Sucumbíos provinces.
Sources: Photographs of SatAgro personalized reports downloaded by farmers.

Figure B.2: Classroom Activities

Exhibit A



Exhibit B



Exhibit C



Exhibit D



Notes: This figure presents documentary evidence of the SatAgro classroom activities involving farmers assigned to the field days treatment.
Sources: Photographs of SatAgro classroom activities for farmers attending the field days.

Figure B.3: Completion Diploma Ceremony



Notes: This figure presents documentary evidence that completion diplomas were awarded to palm farmers who attended all 4 field days.
Sources: Photograph of the completion diploma ceremony for 1 of the 18 small farmer groups assigned to the field days treatment.

Figure B.4: Agricultural Practice Demonstrations

Panel A. Palm Nursery Field Day



B. Pollination Field Day



Panel C. Fertilization Field Day



Panel D. Pest Management Field Day



Notes: This figure presents documentary evidence of the SatAgro tutorials and personalized technical assistance provided to farmers as part of the field days treatment.
Sources: Photographs of the demonstrations conducted as part of the field days.

Figure B.5: SatAgro Tutorials and Personalized Technical Assistance

Exhibit A



Exhibit B



Exhibit C



Exhibit D

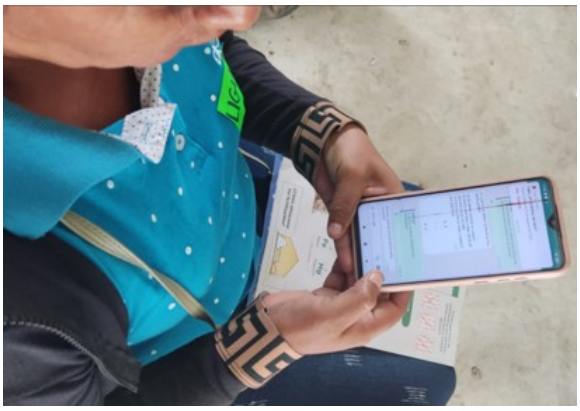


Exhibit E



Exhibit F



Notes: This figure presents documentary evidence of the SatAgro tutorials and personalized technical assistance provided to farmers as part of the field days treatment.
Sources: Photographs of SatAgro tutorials and personalized assistance for farmers attending the field days.