Heeding the Call: How Feedback Mechanisms Shape Farmer Engagement with Digital Extension and Advisory Services in Zambia

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Abstract

Digital extension and advisory services (EAS) are central to efforts to scale information on climate-smart agricultural (CSA) practices, yet how farmers actually engage with these tools and what drives sustained participation remains poorly understood. Using a randomized controlled trial (RCT) of 2,800 smallholder farmers in Zambia, this study examines how interactive feedback opportunities and village-based in-person support shape participation in a digital extension platform. Results indicate that introducing interactive feedback (dynamic content) reduced engagement with static content (pre-recorded messages) by about 66%, as farmers shifted their attention toward the new interactive features. By contrast, complementing the platform with in-person support significantly increased participation across all engagement mechanisms: calling, navigating static content, recording questions, and listening to talk shows. Farmers with access to village-based digital champions were two to five times more likely to participate and did so sooner than others, though this support initially raised dropout risks that diminished over time. Periodic nudges were essential to sustaining engagement over time. These findings highlight the value of hybrid extension models that blend digital tools with community-based facilitation, underscoring the importance of investing in localized support structures to enhance the effectiveness and inclusivity of digital advisory services.

Key words**:** Digital extension, hybrid extension, feedback, participation
JEL classification: Q12, Q16

1. Introduction

In recent years, digitalization has swept across global economies, transforming nearly every sector, including agriculture (World Bank, 2024). Digital technologies hold considerable promise for agricultural development, particularly by improving the dissemination of agricultural information through digital extension and advisory services (EAS), which are among the most commonly used services by farmers who adopt digital technologies for their farming activities (Amoussouhoui et al., 2024). These services can complement traditional agricultural extension and facilitate farmers' access to knowledge and results from scientific research, especially for smallholder farmers in low- and middle-income countries (LMICs), where access to information remains a challenge (Nakasone et al., 2014). Digital EAS present several key benefits, such as the provision of information at low marginal costs per user making them cost-effective at scale (Fabregas et al., 2019). They also create an avenue for two-way information exchange between users and information providers, making it possible to provide farmers with information that is tailored to their needs (Fabregas et al., 2023; Ortiz-Crespo et al., 2021; Steinke et al., 2021).

This study examines how opportunities for interactive feedback and in-person support influence farmer engagement[1] with a digital EAS. The study draws on data from a Randomized Control Trial (RCT) of 2800 smallholder farmers in Zambia who were offered a digital (mobile phone) extension service with information on climate-smart agricultural (CSA) practices[2]. Farmers were randomly assigned to one of five treatment groups that varied in whether they had access to digital interactive feedback mechanisms and/or support from village-based facilitators (digital champions). The treatment groups consisted of 1) access to static content (pre-recorded messages) 2) access to static and dynamic content (interactive feedback) and three distinct hybrid extension models combining the static and dynamic digital content with (1) externally selected facilitators with digital training, (2) externally selected facilitators with digital training and additional training in communication and social inclusion and (3) community selected facilitators. The

[1] In this study, we use the terms *engagement* and *participation* interchangeably.
[2] Information on CSA includes advice on planting, crop management, conservation agriculture, harvesting and marketing, post-harvest handling and winter cropping aimed at improving productivity and adapting to climate change.

randomization ensures that, in expectation, treatment assignment is orthogonal to unobserved farmer characteristics, allowing for causal inference. To analyze farmer engagement with the service, this study employs two complementary econometric approaches using data from a baseline farmer survey and monthly administrative data from a digital services provider (Viamo) on farmers' call frequency and duration and the type of content (i.e., static or dynamic) with which they engaged. First, we estimate a random-effects Poisson model to assess participation intensity measured by the number of times farmers engaged with the service over the study period. Second, we use a Cox proportional hazards model to measure and explain the duration until first participation and participation retention, providing insights into both the timing of uptake and dropout risk. Together, these approaches allow for a comprehensive analysis of farmers' uptake, frequency of use, and sustained participation in digital EAS.

Results show that providing farmers with opportunities to give and receive digital feedback did not increase overall engagement but changed how farmers interact with the service. Farmers reduced their engagement with static content by 66%, as their attention shifted toward more dynamic features of the service. Complementing the digital service with in-person support from village-based digital champions substantially increased engagement across all mechanisms-calling, navigating static content, recording questions, and listening to talk shows. With digital champion support, farmers were between two and five times more likely to engage with the service, highlighting the importance of hybrid extension models over purely digital or purely in-person approaches. These effects were strongest for farmers in the treatment in which community members, rather than extension officers, selected their digital champions. This suggests that community-selected support persons play a critical role in enhancing engagement. These findings align with Jones & Kondylis, (2018), who found that opportunities for feedback sustained farmer participation in group settings. A further result to highlight is that farmers in the treatment where digital champions were trained in trust and social inclusion did not exhibit the fluctuation patterns in calling into the service observed in the other treatments, highlighting the role of trust-building and inclusive facilitation in sustaining engagement. Moreover, hybrid forms of extension accelerated uptake - farmers engaged with content two to five times sooner than those without in-person support, though their dropout risk was higher, but moderated over time.

These findings suggest that digital advisory services are more effective at promoting farmers' engagement when complemented with localized, in-person support, rather than being delivered in isolation. Providing farmers with opportunities to interact, give feedback, and receive guidance from trusted community-based champions significantly enhances uptake and accelerates adoption. Policymakers and practitioners should therefore prioritize hybrid extension models that blend digital content with community facilitation and trust-building, as this approach not only drives initial participation but also sustains engagement over time. Periodic nudges, refresher messages, or interactive campaigns are essential to sustain engagement and prevent dropout once initial curiosity fades.

Several studies have assessed the impact of farmers' use of digital EAS on various agricultural outcomes such as crop yield (Arouna et al., 2021; Van Campenhout et al., 2021), awareness of recommended agricultural practices (Dzanku & Osei, 2023; Fu & Akter, 2016; Fabregas et al., 2024), adoption of recommended agricultural practices (Cole & Fernando, 2021; Larochelle et al., 2019; Lasdun et al., 2025), attitudes towards digital technology use (Fu & Akter, 2016), peer interactions (Fernando, 2021), production decision-making (Aker & Ksoll, 2016) and profits (Arouna et al., 2021). Although the results vary across contexts, the bulk of evidence suggests that digital EAS improve key agricultural outcomes. According to Aker et al., (2016), positive impacts are observed in contexts characterized by high information asymmetry as well as in areas with strong supporting institutions, such as well-functioning credit markets and well-developed infrastructure.

While digital EAS can improve farmers access to information, their unequal distribution tends to exacerbate existing inequalities, leaving further behind those in disadvantaged positions, due to lack of access to necessary resources, poor connectivity or low digital proficiency (FAO, 2023; Roberts & Hernandez, 2019). Bridging this gap is essential for enabling poorer farmers to fully benefit from these services and requires making digital EAS tools accessible, affordable and inclusive in design (Steinke et al., 2024). Inclusivity means centering farmers in the design and delivery of these services, rather than treating them as passive end-users (Coggins et al., 2022). Doing so allows for feedback loops that better address local needs and improves service relevance (Ortiz-Crespo et al., 2021; Steinke et al., 2021). Yet, while the value of co-design in digital EAS is increasingly being recognized, little is known about how farmers engage with these platforms through different interaction modes and over time. This study addresses that gap. Understanding engagement is a crucial first step toward designing more inclusive and farmer-centered digital EAS, since without insights into patterns and the role of feedback, inclusivity risks being a stated goal rather than a realized practice.

This study contributes to three strands of the literature on digital EAS. First, it examines the role of feedback in the demand for digital EAS. Prior work has shown that feedback opportunities can influence outcomes beyond simple one-way information delivery, including maintaining demand for agricultural services, reducing group attrition (Jones and Kondylis, 2018), improving farmers' access to information and knowledge and fostering more positive attitudes toward digital technologies (Fu and Akter, 2016). While these studies focus on knowledge gains and attitudes, this study instead examines how opportunities for feedback directly influence farmers' uptake and continued use of a digital EAS. Understanding farmer use is critical, since consistent engagement with the service is necessary for realizing improvements in outcomes such as knowledge, adoption and productivity.

Second, this study contributes to debates on the effectiveness of hybrid extension systems, where digital EAS are complemented with in-person facilitation. Previous research has found mixed results, including no difference between outcomes of farmers who had access to a purely digital extension service and those who had access to a hybrid service (Cole and Fernando, 2021) as well as improved knowledge, advice acceptance and feedback (Ding et al., 2022). Building on this work, this study moves beyond a simple digital-versus-hybrid comparison. By differentiating among types of in-person facilitation, we identify which hybrid models most effectively improve participation and sustain engagement.

Third, we contribute to the emerging literature on the dynamics of farmer engagement with digital EAS over time. While most existing studies focus on the downstream effects of using these services, such as productivity gains or behavioral outcomes (Arouna et al., 2021; Van Campenhout et al., 2021; Aker & Ksoll, 2016), few studies examine how farmers actually engage with these platforms or how engagement evolves. We address this gap by tracking both the time to initial uptake and the risk of dropout during the study period, offering new evidence on the temporal and behavioral dimensions of participation in digital EAS, an underexplored mechanism through which digital EAS impacts producers.

The rest of the paper is organized as follows. Section 2 presents the study context and experimental design while Section 3 presents a description of the data and the descriptive statistics. Section 4 presents the empirical strategy; Section 5 presents the results and Section 6 presents the discussion and Section 7 presents the conclusion. Finally, Section 8 presents the study limitations.

2. Study Context and Experimental Design

2.1. Background

In many developing countries, agricultural information has traditionally been delivered by the public sector, reflecting its nature as a public good (Fabregas, et al, 2023). Under conventional extension models, scientific research is passed on to extension agents, who then share it with farmers through farm visits, community field days, or training workshops (BenYishay & Mobarak, 2019; Kondylis et al., 2017). Agricultural information and technologies can also be diffused from farmers to other farmers through peer learning and social networks (BenYishay & Mobarak, 2019; Takahashi et al., 2020). While valuable, this model faces well-documented challenges: it is costly, extension agent-to-farmer ratios remain low, and coverage is especially limited in remote areas and among disadvantaged populations (Aker, 2011). Digital technologies offer opportunities to address these constraints by expanding the reach of agricultural information at low marginal cost, including to farmers in geographically isolated regions (FAO, 2021). Beyond scaling delivery, digital platforms also enable two-way exchanges, making it possible to tailor advice to farmers' specific needs (Arouna et al., 2020) In practice, digital extension and advisory services in developing countries are often mobile phone-based, relying on text messaging or interactive voice response (IVR) systems that provide both static messages as well as channels for farmer feedback (Fabregas, 2023). With mobile phone adoption now widespread, the potential for digital extension and advisory services to transform agricultural information delivery in LMICs is considerable (World Bank, 2024).

2.2. The *Atubandike* hybrid advisory service

This study focuses on a hybrid (mobile + in-person) advisory service on climate-smart agriculture (CSA) practices that was developed and piloted by the International Maize and Wheat Improvement Center (CIMMYT) and the mobile service provider, Viamo. *Atubandike* (meaning "Let's Chat" in Zambian language, Tonga) was made available to 2,800 smallholder farmers in Southern Province, Zambia in September 2024. Farmers call into a toll-free, IVR platform on their feature[3] or smart phone and navigate to both static (30 pre-recorded CSA messages) and dynamic content. Dynamic content is regularly updated from farmer feedback as illustrated in Figure 1. Farmers can record questions, share experiences and listen to peer stories, while a multi-stakeholder committee consisting of government representatives, scientists and farmers, translates feedback into biweekly radio talk shows. Village-based digital champions are used to further strengthen trust, build digital literacy, and support timely responses to farming queries. The IVR is available in English and four local languages, making it accessible to farmers who might otherwise be excluded due to limited literacy levels. The CSA content includes information on planting, conservation agriculture, crop management, harvesting and post-harvest handling (for a detailed description, see Figure A1 in the Appendix). By combining digital technology with community-led design, the platform shifts farmers from passive recipients to active contributors in shaping advisory content (CIMMYT, 2025).

The *Atubandike* advisory service aligns well with the goals for agricultural extension in Zambia. The Zambian Ministry of Agriculture recently launched an E-Extension service, aimed at promoting digital innovation and transforming how agricultural information is disseminated (Kiogora et al., 2024). The agricultural sector is crucial to the economy of Zambia, contributing about 2.8% to the country's Gross Domestic Product (GDP) and

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[3] A feature phone is a mobile device that is less sophisticated than a smartphone, with basic functionalities like calling and texting, limited internet access and pre-installed apps.

supporting the livelihoods of about 70% of the population in 2023 (ZDA, 2024). Like many economies in Sub-Saharan Africa, the agricultural sector in Zambia comprises mainly of smallholder subsistence farmers, with limited access to agricultural information: there is one extension agent for every 1000 farmers (Kiogora et al., 2024). Digitizing the provision of extension services will help alleviate this challenge and achieve the overall goal of reaching food security by employing CSA practices.

In the Southern Province, particularly in Kalomo, Choma, and Monze districts, the area covered by this study, farming is predominantly smallholder-based and rainfed, with maize, groundnuts, sunflower, and beans as the main crops. The principal growing season runs from November to April, corresponding to the onset and retreat of the rainy season, followed by a dry winter cropping period from May to August in irrigated or lowland areas. Although the region is relatively productive, recurrent droughts and erratic rainfall patterns have made CSA practices essential for sustaining yields. The *Atubandike* service directly supports this need by delivering localized content on planting, crop management, conservation agriculture, harvesting and marketing, postharvest handling, and winter cropping, helping farmers adapt to climatic variability while improving productivity and resilience.

2.3. Experimental Design

The project was implemented as a Randomized Control Trial (RCT) in three districts in Zambia's Southern Province: Kalomo, Choma and Monze (Figure 2). These districts were purposely selected because of their role in Zambian smallholder agriculture, high climate variability and limited reach by digital advisory services. A multi-stage sampling approach was used to select 2,800 farmers for the study. First, population-proportional-to-size sampling was used to select 10 agricultural camps each in Kalomo and Monze, and 15 in Choma, yielding a total of 35 camps. An agricultural camp, the smallest administrative unit, comprises several villages organized into 4-8 zones. The 35 camps were then randomly assigned, with equal probability, to one of five treatment arms, ensuring balance across groups. We do not have a pure control group as we are not interested in comparisons with a business-as-usual case (Duflo, Glennerster and Kremer, 2006). Randomization was done at camp level to minimize spillover effects. Within each camp, two zones were randomly selected. Finally, intra-household sampling was used to randomly select 40 farmers per zone, resulting in the study sample. Figure 3 illustrates the experimental design.

Farmers randomly assigned to the first treatment (T1), or push digital advisory, have access only to the static, pre-recorded content described earlier. The second arm, T2, adds an interactive component, combining the pre-recorded messages with dynamic content that allows farmers to ask and receive responses to questions and share farming experiences with peers. Treatments T3, T4 and T5 are different variants of hybrid advisory systems incorporating in-person support in addition to access to dynamic and static content via phones. T3 combines T2 with support from village-based digital champions (DCs) selected by community leaders, who receive digital training and ongoing support through weekly coaching calls and a WhatsApp peer learning group. T4 adds a layer of training on communication skills and gender, diversity, and inclusion (GDI) for the DCs, aimed at strengthening trust and promoting inclusivity in DC-famer interactions. The final arm, T5, pairs T2 with wider community engagement. At the start of the project, two community meetings were held to introduce the project and enable community members to nominate and democratically select DCs. Social changemakers were also elected to lead community-driven initiatives and villagers were involved in developing action points for inclusion. DCs and social changemakers receive ongoing coaching and support.

This study analyzes intent-to-treat (ITT) effects on farmer participation in the platform. At the time of writing, the project is still ongoing and additional outcomes, such as the ITT effects of farmers' trust in digital advisory services – will be assessed in subsequent analyses. As shown in Figure 4, the baseline survey was implemented in January-February 2024, while the *Atubandike* digital advisory service and accompanying facilitation components were rolled out in September 2024. The interval between baseline and implementation reflects the participatory action research process through which the platform, feedback mechanisms, and training of digital champions were co-developed with farmers and Viamo. This iterative approach was critical for contextual relevance and technical reliability but extended the rollout timeline. Because the platform was not available to farmers before September 2024, the baseline data are fully pre-treatment and unaffected by exposure to the intervention.

3. Data and Descriptive Statistics

We use two sources of farmer-level data for analysis in this study. The first is the baseline survey data collected in January and February 2024, covering the 2800 intervention farmers. This data includes information on the farmers' socioeconomic and demographic characteristics, agricultural production and awareness and knowledge of CSA practices. The second source is monthly *Atubandike* usage data collected by Viamo from September 2024 through December 2025. We use data up to May 2025 because there was a disruption in the service from June to August 2025. In this dataset, engagement is recorded across six modes: calling, navigating static content, recording questions, listening to talk shows, listening to shared experiences, and recording experiences. Our study focuses on the first four modes of participation, as the latter two were not implemented until the last few months covered by this study (see Table A3 in the Appendix for descriptive statistics). Data on listening to talk shows begins in November 2024, which is when the first talk show was aired based on the questions recorded by the farmers in September and October. Participation variables are coded as binary indicators, counts and duration (for calls) and are linked to treatment arms via household and camp identifiers.

Table 1 shows the demographic and production characteristics of the farmers by treatment group. Female farmers make up a slight majority, ranging from 54.46% to 58.93%. A Chi-square test of significance ($\chi2 = 20.39, p = 0.000$) shows that the proportion of males and females is not perfectly balanced across treatment groups, though the differences are relatively modest in magnitude. The average age is 40 and most have at least a primary school education. Most farmers (about 43%) report that their income is only sufficient to meet expenses. Farmers in the sample are mainly smallholder farmers, who own about 3 hectares of land on average and have been in agriculture for about 3 years on average. All farmers reported growing maize in the 2022/2023 farming season, while over 70% of the farmers grew groundnuts and kept livestock. About 60% of farmers reported receiving agricultural information, mostly from government extension workers. At 79%, mobile phone ownership among the farmers in this sample is well above the 66% average for LMICs, of which Zambia is a part (World Bank, 2024). However, only 4% of farmers report having access to a smartphone, highlighting an affordability gap that *Atubandike* addressed by enabling access via feature phones.

We assess baseline balance by estimating a multinomial logit (MNL) model of treatment assignment against the pre-treatment covariates (Mckenzie, 2024). Let $T_i \in \{1,2, \ldots K\}$ denote the treatment assignment for farmer *i*, where *k* is the number of treatment arms and let $X_i = (x_{1i}, x_{2i}, \ldots \ldots x_{mi})$ represent the vector of pretreatment covariates. The MNL model is specified as:

$$Pr(T_i = k|X_i) = \exp(X_i\beta_k) \,/\, \sum_{j=1}^{k} \exp\,(X_i\beta_k), , k = 1, 2, \ldots 5 \qquad (1)$$

With $\beta_1 = 0$ for the reference group. Equivalently, for *k* = 2,…K, the log-odds of being assigned to treatment *k* relative to the reference group are:

$$\log\,(Pr(T_i = k|X_i)/Pr(T_i = 1|X_i)) = X_i\beta_k \qquad (2)$$

To account for the clustered experiment design, we obtain a randomization-inference (RI) *p*-value by permuting treatment labels at the camp level, preserving the experiment structure. Unlike standard asymptotic inference, this approach evaluates the null hypothesis that treatment has no effect based solely on the randomization mechanism (Kerwin et al. 2024; Abadie et al., 2020). For each permutation, we re-estimate the MNL model and calculate the joint Wald Chi-square statistic for the covariates. Comparing the observed Chi-square statistic (χ^2 = 2539.73) to the distribution generated from 50 permutations, we obtain a RI *p*-value of 0.90. This high *p*-value indicates that the pre-treatment covariates are jointly orthogonal to treatment assignment, providing strong evidence that randomization achieved balance across these variables. All standard errors are clustered at the camp level to account for intra-cluster correlation.

Participation Patterns

A total of 17203 calls were made into the platform by 1810 different farmers over the 9-month period. This translates to about 65% of all farmers in the sample, with 57% of the callers being women. Of the farmers who called, most made one call into the platform in a month. The distributions of the times called and the other participation variables is shown in Figure A2 in the Appendix.

Call duration ranged from 21 seconds to 394 minutes in a month. The average duration per call for each farmer is presented in Figure 5 (see Tables A4 and A5 in Appendix for detailed descriptives and pairwise mean comparisons). Average call duration differed significantly across treatment groups ($F(4, 6487) = 25.00, p < 0.001$), with T1 having the lowest (7.5 minutes) and T5 having the highest (10.7 minutes). Comparison of means tests showed that farmers in T2-T5 had significantly longer calls than those in T1. Farmers in T5 also showed marginally longer calls than those in T3, while differences among T2-T4 were not statistically significant. This suggests that both dynamic content and digital champions trained in social inclusion produce similar average call durations. Interactive feedback and hybrid facilitation contributed to sustained engagement, with the strongest effect observed under community selection.

These results reflect increasing levels of engagement associated with the both the interactive feedback mechanisms and hybrid extension models, in the form of support from trained facilitators and community sensitization. This likely facilitated deeper or more sustained interactions between farmers and the digital advisory system. There is a noticeable spike in call duration in December for the farmers in T2-T5, probably due to November being the month when the first talk show was aired which could have encouraged more listening in subsequent months.

Figure 6 shows the proportion of farmers who engaged with the digital advisory platform in various ways at least once over the 9-month study period. About 26% of farmers called into the platform in a month (see Table A1 in Appendix for detailed descriptives). After calling into the service, the most accessed service was listening to talk shows (about 16% of farmers in a month), followed by navigating static content (13%) and recording questions (11%). Engagement with the platform was highest in September, when the service launched, perhaps due to initial enthusiasm and outreach. In October, there is a noticeable drop, with the proportion of farmers calling into the platform declining by about 13 percentage points from September. A similar pattern is observed for the other engagement modes. Participation gradually recovered until February, when there is another spike, following renewed outreach and awareness campaigns. After February, participation declined slightly across all forms of participation, though remained higher than in October. Cole & Fernando (2021) find similar patterns among farmers who used a mobile-phone based information service, with usage trending down after the initial months, then fluctuating thereafter depending on seasonal and knowledge needs. These results suggest that farmers have interest in engaging with digital advisory content, but sustained engagement requires periodic nudges, additional support or renewed motivation.

Figure 7 shows the proportion of farmers who participated in the platform over the months, disaggregated by treatment group. As farmers in Treatment 1 only had access to static content, "navigating static content" was their only way to engage with the platform. Participation levels in Treatments 1 and 2 were consistently low, with about 10% of farmers engaging with the digital content. The addition of in-person support from facilitators in Treatments 3, 4 and 5 substantially increased engagement, relative to the purely digital Treatments (T1 and T2), with calling rates of 31–40% compared to 10–11% for the latter. Treatment 5, which included support from community-selected DCs, registered the highest participation levels for calling, navigating static content and listening to talk shows. The Chi-square statistics are statistically significant at the 1% level for all participation variables over time and across treatment groups, confirming the differences in participation rates across treatment groups.

An average of about 40% of farmers in Treatment 5 called over the eight-month period, peaking at 52% in September. Notably, in Treatment 4, the share of farmers calling rose steadily after the initial October decline, even as it fell in other groups, suggesting that training support personnel in social inclusion can help sustain farmer interest over time, preventing the fluctuations seen in other groups. Also of note is that participation through static content navigation increased slightly over time in Treatments 3, 4 and 5 as calling and other modes of engagement declined, indicating a modest shift in how farmers interacted with the platform over time away from interactive engagement towards more self-directed exploration of content.

Participation by sex

Figure 8 illustrates the composition of the participants by gender. Overall, participation rates between female and male farmers were broadly similar across activities, with women accounting for slightly more than half of the participants in each category (56–58%). We observe a weak but statistically significant difference between female and male farmers in calling patterns *($\chi2 = 3.84$ $p=0.050$)*. This may reflect women's greater inclination toward interactive engagement or social support through the service. By contrast, no gender gaps were detected with regards to navigating static content, recording questions and listening to talk shows, suggesting relatively equal uptake of digital content once farmers accessed the platform. Given the absence of systematic gender differences, we did not pursue further decomposition analyses.

This observed pattern contrasts sharply with much of the existing literature on digital EAS, which often finds that men are more likely to access and engage with these services (Abate et al., 2023; Voss et al., 2021). Gender disparities in digital inclusion are typically attributed to lower phone ownership, literacy barriers, and limited decision-making power among women farmers (Tauzie et al., 2024). The near-equal participation observed in this study represents a notable departure from prevailing trends. It suggests that the *Atubandike* platform, by leveraging voice-based communication, localized content, and community-based facilitation, may have reduced structural and social barriers to women's participation. This equitable reach underscores the potential of inclusive design of digital EAS to promote more gender-balanced access to agricultural information and strengthen women's agency within rural innovation systems.

4. Empirical Strategy

4.1 Participation in the digital advisory platform

We estimate the intent-to-treat (ITT) of participation in the platform, analyzing farmers according to their camp-level treatment assignment, regardless of their actual engagement with the platform. This preserves the integrity of the randomization and captures the causal effect of being offered the intervention (Gertler et al., 2016; Duflo et al., 2006). The identification strategy relies on the random assignment of camps to the treatment groups.

To evaluate the impact of the various treatments on farmer participation in the platform, we use a Poisson regression model, which is well suited to count variables such as our dependent variable, which is measured as the number of times a farmer engaged with the platform (Hilbe, 2014). The Poisson regression model assumes that the distribution of the dependent variable, y, conditional on x has the following density:

$$f(y_i|\boldsymbol{x_i}) = e^{-\mu_i}\mu_i^{y_i}/y_i! \tag{3}$$

and mean parameter $\mu_i = \exp(\boldsymbol{x}_i'\boldsymbol{\beta})$, where: y_i is the outcome of interest, $\boldsymbol{x_i}$ is a vector of covariates and $\boldsymbol{\beta}$ the corresponding vector of parameters. The conditional mean is given by $E[y_i|\boldsymbol{x_i}] = \exp(\boldsymbol{x}_i'\boldsymbol{\beta})$, which is assumed to be equal to the conditional variance, a statistical property known as equidispersion. The model is estimated using a maximum likelihood estimator (MLE) and the log likelihood function is given as:

$$L(\boldsymbol{\beta}) = \sum_{i=1}^{n}\{y_i\boldsymbol{x}_i'\boldsymbol{\beta} - \exp(\boldsymbol{x}_i'\boldsymbol{\beta}) - \ln y_i!\} \tag{4}$$

The Poisson MLE, $\widehat{\boldsymbol{\beta}}$, is obtained by differentiating the log likelihood function with respect to $\boldsymbol{\beta}$ (Cameron & Trivedi, 2013). This can be generalized to panel data. Figure 2A in the Appendix shows histograms for the dependent variables we use in the study. The distributions show a large number of zeros, and a long right tail, which is a common feature of count data (Cameron & Trivedi, 2013). We evaluate the impact of the treatment on four modes of participation namely, the number of calls, navigations across static content, times a question was recorded, and times talk shows were listened to.

A random-effects Poisson regression model is used to estimate the conditional expectation of farmer participation, while isolating the effect of the treatment. This can be represented as:

$$E[y_{it}|\boldsymbol{x_{it}}, \alpha_i] = \exp(\boldsymbol{x}_i'\boldsymbol{\beta} + \alpha_i) \tag{5}$$

Where y_{it} denotes the count of participation events for household *i* in month *t*. $\boldsymbol{x_{it}}$ is a vector of covariates including dummy variables for treatment group, month and district, $\boldsymbol{\beta}$ is the corresponding vector of covariates and α_i is the household-specific random effect capturing unobserved heterogeneity.

Because treatment was randomly assigned across clusters, the random-effects Poisson estimator is appropriate for estimating the its effect on count outcomes. Random assignment implies that household-level unobservables are, in expectation, orthogonal to treatment status. This makes the random-effects assumption that the individual effect is uncorrelated with the regressors more plausible for the treatment indicator.

Further, the treatment assignment does not vary over time for each farmer. In a fixed-effects framework, time-invariant variables, such as the treatment in this case, would be eliminated by differencing out and thus cannot be estimated. The random-effects model permits direct estimation of the treatment coefficient while remaining consistent with the randomized design. This approach enables the estimation of the impact of treatment while accounting for both observed controls and unobserved farmer-specific effects.

Our random-effects Poisson regression model specification includes month fixed effects to control for common time shocks, and we allow for treatment-by-month interactions to capture differential participation trends across treatment arms as shown below. Standard errors are clustered at the camp level to account for within-cluster correlation.

$$y_{it} = \beta_0 + \beta_1 \, treat_i + \beta_2 \, month_t + \beta_3 \, district_i + \beta_4 \, treat_i * month_t + \mu_i + \varepsilon_{it} \tag{6}$$

Where y_{it} is the outcome variable - the number of times farmer *i* participated in the platform in month *t*, $treat_i$ is the time-invariant treatment assignment for farmer *i*, $month_t$ represents month-fixed effects (baseline temporal heterogeneity) to control for time-specific shocks, $district_i$ represents fixed effects for the district the farmer *i* lives in to control for unobserved, time-invariant differences across locations, the $treat * month$ interaction allows the treatment to vary over time, μ_i captures farmer-specific heterogeneity as a random effect and ε_{it} is the idiosyncratic error term.

We do not include socio-economic control variables in the main specification due to little explanatory power and multicollinearity concerns that are described in further detail in the results section.

4.2 Time to First Participation and Participation Retention

To measure the impact of feedback opportunities and digital champions on farmer participation in the platform over time, we analyze both farmer retention as well as time to first participation in the platform using duration analysis. Duration models are well suited for studying the timing and probability of events, as they estimate the likelihood that an event occurs at time t given that it has not occurred yet. In this context, two distinct events are of interest: (i) first participation-the month in which a farmer first engages with the platform, and (ii) dropout-the point at which a farmer stops engaging with the platform after initially participating.

For the retention model, the duration (or spell length) is the number of months a farmer remains active before dropping out. For the first participation model, the duration represents the time elapsed from the start of observation until initial engagement with the service. In both cases, farmers who do not experience the event by the end of the study period are treated as right-censored observations (Kiefer, 1988; Wooldridge, 2010). We therefore seek to understand the probability that a farmer experiences a given participation event, either dropping out or first engaging with the service, by the end of the study period, conditional on not having done so earlier. The probability distribution of the duration is specified as:

$$F(t) = \Pr\,(T < t) \tag{7}$$

Where T denotes the time measured in months until the event occurs. The corresponding survival function is given by:

$$S(t) = 1 - F(t) = \Pr(T \geq t), \tag{8}$$

representing the probability that a farmer continues without experiencing the event beyond time t. If we denote the density of T as $f(t) = dF(t)/dt$ and $P(t \leq T < t + h|T \geq t)$ as the probability that the event occurs within the short interval $[t, t + h)$, given survival up to time t (Wooldridge, 2010), then the hazard function is defined as

$$\lambda(t) = \lim_{h \to 0} P(t \leq T < t + h|T \geq t)\,/h, \tag{9}$$

The hazard function thus represents the instantaneous rate at which farmers experience the event (dropout or first participation) per unit of time, conditional on not having done so yet. It provides a continuous-time measure of event risk and serves as the foundation for estimating proportional hazard models (Wooldridge, 2010).

Proportional hazard models allow for the inclusion of time-invariant regressors in addition to estimating the hazard function. We estimate a Cox proportional hazard model, a semi-parametric method that allows the baseline hazard to remain unspecified while modeling the effect of covariates multiplicatively on the hazard rate. The model is expressed as:

$$\lambda(t|\boldsymbol{x}) = \lambda_0 (t) \exp (\boldsymbol{x}'\boldsymbol{\beta}) \tag{10}$$

Where $\lambda(t|\boldsymbol{x})$ is the hazard function at time t for a farmer with covariates $\boldsymbol{x}$, $\lambda_0 (t)$ is the unspecified baseline hazard function and $\exp(\boldsymbol{x}'\boldsymbol{\beta})$ captures the proportional change in the hazard associated with the covariates. This specification enables us to estimate relative risks of dropout and likelihood of initial adoption over time, while avoiding assumptions about the exact shape of the baseline hazard.

Farmers can drop out of the platform and later resume participation in subsequent months. To account for these repeated participation spells, we extend the hazard model to allow for multiple spells per farmer. Each spell is treated as a separate observation with its own start and stop times $[t_{start}, t_{stop})$, while still linking spells to the same farmer. The Cox model generalizes as:

$$\lambda_{ij} (t|x_{ij}) = \lambda_0 \exp (\boldsymbol{x_{ij}}'\boldsymbol{\beta}) \tag{11}$$

Where *i* indexes the farmers and *j* indexes spells. This framework accounts for the possibility that a farmer may re-enter the platform multiple times and allows the hazard rate to vary across spells while controlling for covariates specific to each spell. The model assumes that a farmer's unobserved characteristics remain constant across all of their spells.

Since tests of the proportional hazards assumption indicated that treatment effects were not constant over time, we further extend the model to allow for time-varying coefficients for treatment status. In this specification, treatment indicators are interacted with time, such that:

$$\lambda_{ij}\,(t|x_{ij}) = \lambda_0 \exp\,(\,\boldsymbol{x_{ij}}'\boldsymbol{\beta} + \, z_{ij}\,(t)'\gamma) \tag{12}$$

where z_{ij} represents the interaction between treatment assignment and elapsed time. This allows the hazard ratio associated with treatment to change dynamically as participation unfolds, capturing how the effect of treatment attenuates or strengthens over time.

5. Results

5.1 Results for participation in the platform

Table 2 presents the results of four separate Poisson regressions, each using a different measure of participation in the digital advisory platform as the dependent variable. The reported coefficients are incident rate ratios (IRRs), which indicate the proportional change in the expected count of the outcome associated with each independent variable (Hilbe, 2014). Percentage changes are calculated as (IRR-1) * 100.

To assess the effect of adding feedback mechanisms (dynamic content) on farmer engagement relative to providing only static content, we compare the IRRs of T2 relative to T1. For calls into the platform, the coefficient is close to 1 and statistically insignificant (p < 0.05), indicating that farmers called roughly the same number of times whether they had access to static content only or also to dynamic content. In contrast, farmers in T2 made 66% fewer navigations across static content compared to those in T1, a difference that is statistically significant. Overall, adding feedback mechanisms shifts the type of engagement, away from static toward dynamic content, rather than increasing its intensity.

The impact of digital champions on farmer participation in the platform is assessed through comparisons of the IRRs of T3, T4 and T5 with those of T1 and T2. Relative to those in T1, they called into the platform about 4-6 times more often and navigated static content up to three times more often. These estimates capture the total impact of combining dynamic content with digital champions. When compared to T2 (static + dynamic content), the incremental effect of digital champions is even more striking. Farmers in T3, T4 and T5 made 3-5 times more calls and nearly 5-9 times more navigations than those in T2. They recorded 2-3 times as many questions and listened to about twice as many talk shows. Taken together, results indicate that digital champions strongly boost participation across all modes of interaction. The effect is greatest when champions are democratically selected, as in Treatment 5, underscoring the importance of community ownership in driving engagement. Treatment 4, which included trained external digital champions, showed slightly lower but still substantial effects across the same outcomes. Figure 9 presents a coefficient plot that summarizes these results.

The month fixed effects reveal a general decline in engagement over time compared to September. In further months we observe some fluctuations, for example, there are significant spikes in February and March, especially with regards to navigating static content and calling, coinciding with renewed outreach. Participation in recording questions and listening to talk shows remained low compared to the initial months. District fixed effects reveal that farmers in Monze were significantly more engaged across all outcomes compared to those in Choma, while Kalomo showed no significant differences.

The interaction terms between treatment and month capture how treatment effects evolved over time relative to the baseline. Significant negative interactions for T3-T5 during from February to April suggest that engagement intensity declined relative to the baseline trend, consistent with diminishing novelty effects or seasonal fatigue. In contrast, early-month (Sept) and late-month (May) interactions were smaller or positive, indicating periods of renewed activity. These dynamic effects suggest that the influence of digital champions and feedback mechanisms was strongest immediately after rollout but attenuated over time, and experienced periods of uptick, likely coinciding with check-ins with the digital champions.

Adding socioeconomic control variables (e.g. age, income, education level) did not meaningfully change the magnitude or direction of treatment effects, although standard errors widen considerably (Full results presented in Table A7 in Appendix). This suggests that these covariates contribute little explanatory power and may introduce multicollinearity. This is consistent with the randomized design, which indicates that the observed treatment effects are not driven by underlying demographic or economic differences (Cameron, 2024; Gertler et al., 2016). Given that treatment assignment was randomized, the main results are reported without these controls.

5.2 Results for participation retention

Table 3 reports the Cox proportional hazards regression results for treatment on dropout risk for the four modes of participation. Results show that relative to farmers in T1, those in T3, T4 and T5 face significantly higher risk of dropping out with regards to making calls or navigating static content. Hazard ratios range from 3.1 to 4 for calls and from 3.4 to 5.3 for static content, suggesting that farmers in T3-T5 are three to five times more likely to disengage in a given period compared to those in T1. Farmers in T3-T5 are also 2-3 times more likely to disengage from calling compared to those in T2. This is obtained by estimating the regression with T2 as the base. The same farmers are between 3 and 5 times more likely to drop off from navigating static content compared to those in T2. Farmers in T4 and T5 are about 2 and 3 times more likely to stop recording questions than those in T2, while farmers in T5 are twice as likely to stop listening to talk shows than those in T2. The time-varying interactions provide additional nuance. For most outcomes, the treatment effects are relatively stable over time, as interaction terms are close to one and not statistically significant. The main exception is static content, where hazard ratios for T3 and T5 decline significantly over time. This suggests that while digital champions induce initially high churn in static content, their dropout risk moderates as the program progresses.

Figure 10 illustrates the dropout risk. Each panel depicts the cumulative probability of dropout from the digital advisory platform. Curves correspond to treatment groups. Across most interaction modes, treatments with digital champions (T3-T5) exhibit higher initial engagement followed by faster early dropout, consistent with greater exposure but shorter participation spells. In contrast, the static-content panel shows a lower cumulative dropout curve for T2, indicating that farmers accessing only static and dynamic content (without champions) tended to sustain engagement for longer periods, even if overall participation levels were lower.

Overall, these findings indicate that digital champions substantially increase participation but also accelerate dropout hazards, particularly in the early stages. Over time, however, these elevated risks diminish for static content, pointing to a pattern of initial enthusiasm followed by stabilization.

5.3 Results for time to first participation

Table 4 presents the Cox proportional hazards regression results for treatment on time to first participation. Across all modes of participation, the inclusion of digital champions substantially accelerated farmers' initial engagement with the platform. Farmers in T3-T5 were four to five times more likely to make their first call and two to three times more likely to first navigate static content relative to those in T1. Compared to farmers in T2, those in T3-T5 were three to four times more likely to first call and three to five times more likely to first navigate static content. A similar pattern is observed for recording questions and listening to talk shows, where farmers in T3, T4 and T5 were two to four times more likely to participate earlier than those without support from digital champions.

Figure 11 illustrates the cumulative share of farmers who engaged with the platform for the first time, estimated using Kaplan–Meier methods. From the figure, we see that across all participation modes, farmers in T3-T5 reached their first interaction substantially earlier than those in the T1 and T2. By December, roughly half of farmers in T3–T5 had already called or navigated the platform, compared to fewer than one-quarter in T1 and T2. These results highlight the strong early mobilization effect of hybrid, community-supported digital extension models.

The time-varying coefficients show that these effects are strongest early in the observation period and gradually wane over time. In particular, the interaction term for T1 is below 1 and significant for calls, static content and recording questions, indicating that the initial advantage of community-selected champions declines slightly as adoption saturates. In contrast, the effect of providing dynamic content alone (T2) does not significantly change the timing of first participation. Overall, the results suggest that the presence of trusted, community-based digital champions substantially accelerates early engagement with the service, even if their marginal impact diminishes as participation broadens.

6. Discussion

This study provides new evidence on how interactive feedback mechanisms and hybrid facilitation models influence farmer engagement with digital extension services, using results from an RCT conducted among smallholder farmers in the Southern Province of Zambia. Across nine months of implementation, about two-thirds of farmers in the sample engaged with the platform at least once, indicating broad interest in digital advisory tools. Participation patterns reveal fluctuations, depending on seasonal needs and periodic nudges. Results also reveal that facilitating engagement requires more than digital access - it depends on the design of interactive features and the presence of trusted human facilitators.

We find that the inclusion of two-way interactive digital feedback features (dynamic content) does not boost overall engagement, however, it does change how the farmers participate in the service. Farmers in the feedback-enabled treatment were no more likely to engage than those in the static-only group, but they substituted away from static content toward dynamic content. This suggests that while feedback options attract farmers' attention, they may not inherently increase intensity of use unless coupled with reinforcement or follow-up. The finding complements earlier studies showing that feedback improves knowledge and attitudes (Fu & Akter, 2016) and increases farmer demand for group services (Jones & Kondylis, 2018). From a policy perspective, this implies that interactivity alone is insufficient to sustain engagement.
To make two-way features more effective, feedback must be paired with timely responses, personalized follow-up or social reinforcement mechanisms such as call-back systems, or champion-mediated outreach. In other words, interactivity should not be treated as a stand-alone design upgrade but rather as part of a broader engagement strategy that maintains farmer motivation and closes the feedback loop.

Introducing persons to support farmers (digital champions) markedly increased engagement, adding to the mixed evidence on the effectiveness of digital-physical ("phygital") models in boosting outcomes (Cole & Fernando, 2021; Ding et al., 2022). Farmers in treatments with digital champions made 3-5 times more calls into the platform and up to 8 times more engagements with static content than those who had access to digital content only, capturing the incremental effect of adding digital champions. These same farmers engaged with the dynamic features of the service twice as much. The magnitudes of these effects were greatest when facilitators were community-selected, highlighting the role of local ownership in technology diffusion. When the digital champions received communication and inclusion training, we observe gradual improvements in calling into the service over time, suggesting that trust-building and inclusive facilitation can mitigate participation fluctuations and decline. These results extend the mixed evidence on hybrid systems by identifying which types of facilitation matter most: community-embedded and socially skilled facilitators appear to sustain engagement more effectively than externally assigned ones. This is consistent with Gallardo et al., (2018), which states that community development efforts in the digital era need to have the support of local, trusted facilitators or champions, in addition to being driven by the communities themselves.

The strong performance of treatments involving digital champions highlights the importance of embedding human facilitation within digital extension systems. Policymakers should consider integrating community-selected, well-trained facilitators into digital advisory programs to build trust, sustain engagement, and enhance inclusivity. This can yield higher and more equitable returns than purely digital solutions, especially in low-literacy or trust-constrained environments.

By analyzing time-varying participation and dropout hazards, this study adds a dynamic perspective to the digital extension literature, which has largely focused on static adoption outcomes. Engagement exhibited a typical novelty pattern, with high initial participation, a subsequent decline, and renewed activity following renewed outreach, patterns consistent with temporal engagement trends observed by Cole & Fernando (2021). Treatments involving digital champions accelerated both first participation and early dropout, revealing that while champions mobilize farmers quickly, maintaining momentum requires continuous motivation. This highlights the difference between uptake and retention in digital extension. Over time, however, dropout risk among hybrid groups moderated, particularly for static content, suggesting adaptation and stabilization once farmers became familiar with the system. This suggests that repeated exposure and routine use transform novelty-driven engagement into more self-directed learning. Policymakers can leverage this finding by integrating structured follow-ups, periodic incentives and adaptive digital content that refreshes farmers' interest and learning opportunities. Embedding behavioral nudges or progressive content can help convert early participation into long-term, self-sustained engagement, strengthening the overall resilience and inclusivity of digital extension systems.

Female farmers constituted a slight majority of participants, and the small but significant difference in calling behavior suggests women's relatively higher inclination toward interactive or community-supported engagement. The absence of strong gender gaps across other activities is encouraging, indicating that the digital platform and facilitation model did not reproduce gender barriers often found in agricultural extension (see also Fu & Akter, 2016). From a policy standpoint, this underscores the importance of embedding inclusive design principles such as accessible interfaces, and trusted local facilitators, into national digital extension strategies to ensure that technological innovations translate into equitable benefits.

7. Conclusion

This study contributes to the growing literature on digital agricultural extension by showing how interactivity and human facilitation jointly shape participation dynamics. Using high-frequency engagement data from a randomized evaluation in Zambia, the results demonstrate that the design of feedback features and the inclusion of community-based facilitators both significantly influence how farmers interact with digital advisory platforms. While digital champions were highly effective in catalyzing early engagement, their impact tapered as participation stabilized, suggesting that sustained use depends on habit formation rather than novelty. At the same time, the finding that feedback mechanisms altered participation patterns without increasing overall engagement underscores the need for complementary social and behavioral components in digital extension design. These insights signal that effective digital inclusion requires not only technological innovation but also thoughtful integration of human and behavioral elements.

Future research could deepen understanding of the mechanisms underlying these participation dynamics. For instance, linking engagement data to behavioral and welfare outcomes would help clarify whether early participation and sustained use translate into measurable improvements in knowledge, adoption, or productivity. Examining the social diffusion of engagement, e.g. through peer networks, local leadership, or group learning, could reveal how information and behavior spread beyond treated farmers. Methodologically, future studies could combine experimental and observational approaches to explore how digital and human components interact under varying levels of infrastructure and institutional support. This will help refine how digital extension programs can balance efficiency with inclusivity and long-term impact.

8. Study limitations

While the findings of this study provide strong evidence on participation dynamics in digital extension services, several limitations should be acknowledged. First, the analysis is restricted to engagement behavior and not downstream impacts such as learning, technology adoption, productivity, or welfare outcomes. Understanding whether and how participation translates into tangible improvements remains an important next step.

Second, while the study highlights the effectiveness of digital champions in boosting farmer engagement with a digital EAS, it does not examine their cost-effectiveness or sustainability once project support ends. Future work could evaluate alternative facilitation and incentive structures, comparing public, private, and community-based delivery models. Such analyses would provide valuable guidance for policymakers designing national digital extension programs that balance scale, inclusion, and long-term financial viability.

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Tables

Table 1: Farmer pre-treatment characteristics by treatment assignment

Variable	Total (N=2800)	T1 (n=560)	T2 (n=560)	T3 (n=560)	T4 (n=560)	T5 (n=560)
Panel A: Demographic Characteristics						
Age (years)	39.61 (16.24)	38.77 (16.50)	39.79 (15.91)	39.97 (15.80)	40.15 (16.37)	39.40 (16.61)
Female (%)	56.32	54.46	58.93	56.79	55.71	55.71
Household size	6.41 (2.92)	6.11 (2.94)	6.40 (2.68)	6.59 (2.91)	6.51 (3.08)	6.42 (2.94)
Years lived in zone	24.62 (16.87)	23.21 (16.13)	24.99 (16.44)	25.89 (17.66)	25.40 (17.03)	23.64 (16.90)
Income sufficiency (%)						
Allows to build savings	3.21	1.96	4.29	2.68	5.71	1.43
Allows to save a little	22.82	22.50	24.82	19.46	23.04	24.29
Only meets expenses	43.75	48.75	40.89	46.07	44.46	38.57
Not sufficient	12.21	7.86	14.29	13.75	9.46	15.71
Really not sufficient (have to borrow)	18.00	18.93	15.71	18.04	17.32	20.00
Education level (%)						
None	2.79	2.50	2.32	3.93	2.32	2.86
Lower Primary	11.43	7.86	13.21	10.36	12.68	13.04
Upper Primary	40.46	41.25	39.82	41.07	39.11	41.07
Junior Secondary	28.46	31.07	26.79	27.14	29.11	28.21
Senior Secondary	15.43	16.25	15.71	16.07	15.18	13.93
Trade Certificate	0.29	0.36	0.54	0.18	0.18	0.18
Tertiary	1.14	0.71	1.61	1.25	1.43	0.71
Marital status (% of farmers)						
Single	12.61	14.82	14.29	11.07	11.61	11.25
Married (monogamous)	54.64	51.07	56.43	55.36	56.96	53.39
Married (polygamous)	15.04	16.25	12.50	15.89	15.71	14.82
Cohabiting	0.18	0.00	0.54	0.18	0.00	0.18
Widowed	7.96	8.04	6.96	8.39	7.32	9.11
Divorced	8.25	8.21	7.86	8.04	7.68	9.46
Separated	1.32	1.61	1.43	1.07	0.71	1.79
Panel B: Agricultural Activity						

Years in agriculture	3.49 (0.77)	3.46 (0.78)	3.52 (0.76)	3.53 (0.75)	3.54 (0.75)	3.41 (0.81)
Land area (ha)	2.94 (2.97)	2.69 (2.44)	2.89 (2.86)	3.33 (3.89)	2.79 (2.16)	3.03 (3.18)
Land ownership						
Own land (%)	84.82	85.71	83.57	83.04	86.07	85.71
Rented land (%)	13.89	11.96	14.64	17.32	14.11	11.43
Communal land	37.00	32.14	37.68	45.18	34.46	35.54
Borrowed land	19.11	21.07	13.57	20.36	18.93	21.61
Production in 2022/23 season (% of farmers)						
Maize	100	100	100	100	100	100
Soyabeans	13.54	8.93	16.43	17.68	8.21	16.43
Groundnuts	73.00	68.93	68.57	82.14	71.07	74.29
Own Livestock/poultry	95.68	97.50	93.21	96.25	96.07	95.36
Credit access						
Receive credit from friends/relatives	48.07	48.04	39.82	50.54	47.32	54.64
Receive credit from microfinance	15.96	13.57	23.93	11.25	17.86	13.21
Panel C: Access to information (%)						
Own radio	44.11	38.93	51.79	42.32	45.89	41.61
Own TV	13.14	11.79	19.29	9.82	15.18	9.64
Own mobile phone	79.39	78.39	78.57	79.64	80.36	80.00
Access to smartphone	4.07	3.57	0.71	4.11	8.04	3.93
Received agricultural advice in 2022/23 season	60.36	58.75	56.43	57.86	64.46	64.29
Received advice from government extension	40.65	41.34	38.92	44.75	45.71	32.78
Received advice through phone	12.46	12.68	12.68	11.61	13.93	11.43

Standard deviations are in parentheses

Table 2: Random-effects Poisson regression results of participation against treatment

	Calls	Navigations of static content	Recorded questions	Talk shows listened to
	Treatments (base: T1)		*Treatments (base: T2)*	
T2	1.119 (0.204)	0.336*** (0.086)		
T3	4.741*** (0.572)	1.594** (0.298)	2.760*** (0.660)	1.981*** (0.409)
T4	3.814*** (0.635)	1.757** (0.409)	1.632** (0.368)	1.834** (0.438)
T5	5.691*** (0.674)	3.008*** (0.580)	3.530*** (0.760)	2.239*** (0.583)
Districts (base: Choma)				
Kalomo	0.967 (0.023)	0.972 (0.026)	1.018 (0.054)	1.052 (0.065)
Monze	1.770*** (0.120)	1.849*** (0.078)	1.386*** (0.129)	1.720*** (0.226)
Treat*month	Included	Included	Included	Included
Constant	0.204*** (0.019)	0.636*** (0.107)	0.257*** (0.045)	0.177*** (0.030)
Number of observations	25 200	25 200	20 160	15 680

*The regression includes all treatment-by-month interactions (Treat × Month). Coefficients for these interactions are not shown individually in this table for brevity. Coefficients represent the incident rate ratios (IRRs); Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Table 3: Cox proportional Hazard regression results for dropout risk

	Dependent Variables			
	Calls	**Navigation of static content**	**Recorded questions**	**Talk shows listened to**
	Treatments (base: T1)		*Treatments (base: T2)*	
T2	1.355 (0.278)	0.962 (0.362)		
T3	3.410*** (6.708)	4.653*** (1.544)	2.611 (0.827)	1.598 (0.499)
T4	3.071*** (0.517)	3.389*** (1.161)	2.272** (0.772)	1.518 (0.525)
T5	4.018*** (0.519)	5.340*** (1.535)	3.252*** (1.110)	2.133** (0.629)
Time-varying effects				
T2*month	0.984 (0.041)	0.958 (0.055)		
T3*month	0.988 (0.025)	0.911** (0.041)	0.983 (0.049)	1.106 (0.084)
T4*month	0.986 (0.032)	0.941 (0.043)	0.976 (0.059)	1.108 (0.087)
T5*month	0.970 (0.025)	0.906** (0.037)	0.930 (0.050)	1.075 (0.078)

*Results are robust to controlling for district heterogeneity. Adding district indicators (or stratifying by district) leaves the treatment hazard ratios essentially unchanged, consistent with randomization; clustered standard errors in parentheses are at the camp level; *** p<0.01, ** p<0.05, * p<0.1*

Table 4: Cox proportional Hazard regression results for time to first participation

	Dependent Variables			
	Calls	Navigation of static content	Recorded questions	Talk shows listened to
	Treatments (base: T1)		*Treatments (base: T2)*	
T2	1.233	0.644		
	(0.407)	(0.235)		
T3	3.983***	2.194**	2.760***	2.217*
	(0.985)	(0.689)	(0.958)	(1.010)
T4	4.286***	2.227***	2.686***	2.189
	(1.267)	(0.666)	(0.957)	(1.043)
T5	5.614***	3.721***	3.852***	2.897**
	(1.311)	(0.949)	(1.500)	(1.274)
Time-varying effects				
T2*month	1.014	0.978		
	(0.053)	(0.066)		
T3*month	0.984	0.990	0.962	1.043
	(0.030)	(0.039)	(0.062)	(0.151)
T4*month	0.926	0.963	0.934	1.040
	(0.047)	(0.039)	(0.066)	(0.157)
T5*month	0.926***	0.911***	0.883*	1.033
	(0.025)	(0.032)	(0.063)	(0.152)

*Results are robust to controlling for district heterogeneity. Adding district indicators (or stratifying by district) leaves the treatment hazard ratios essentially unchanged, consistent with randomization; clustered standard errors in parentheses are at the camp level; *** p<0.01, ** p<0.05, * p<0.1*

Figures

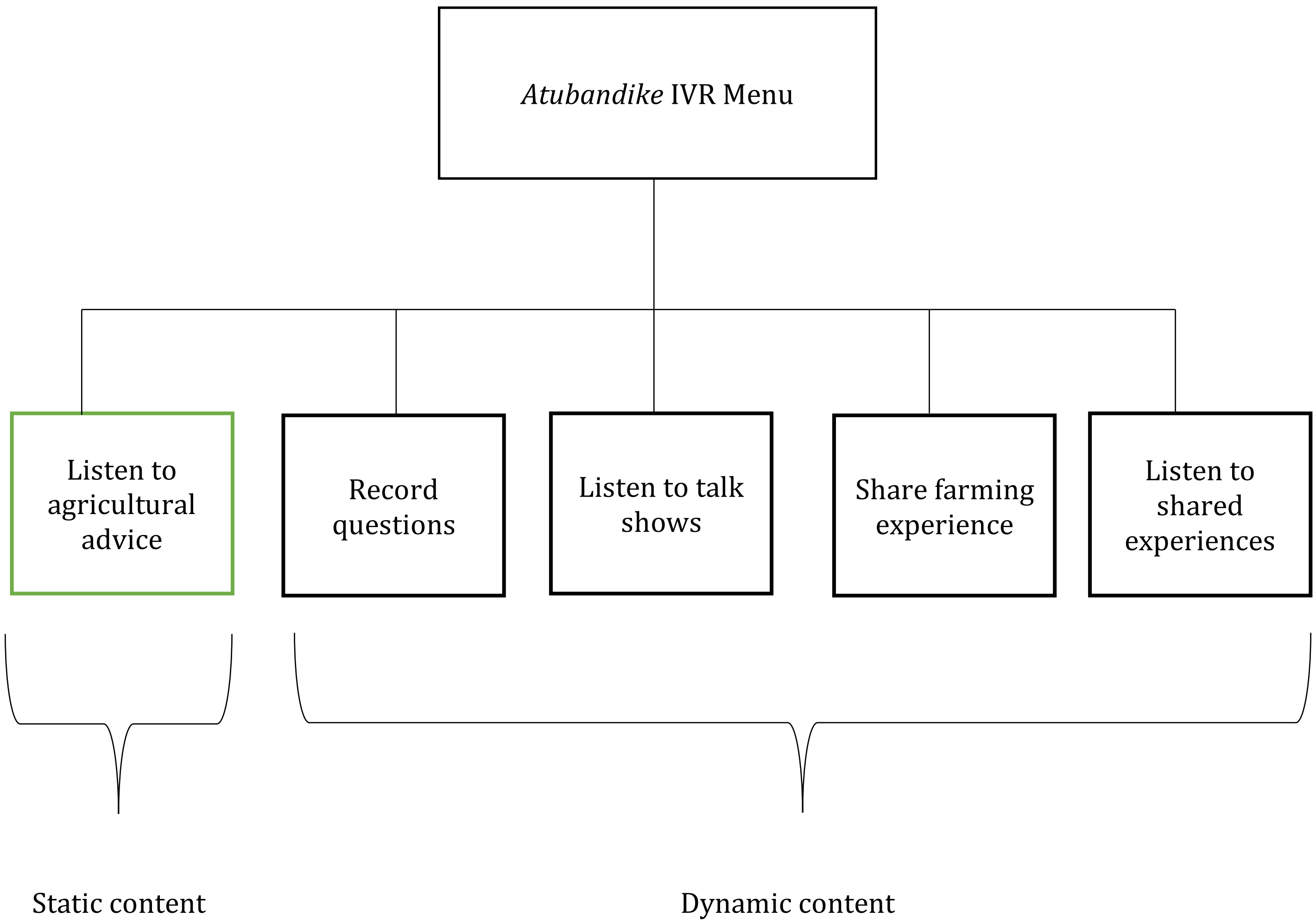

Figure 1: ***Atubandike* IVR system**

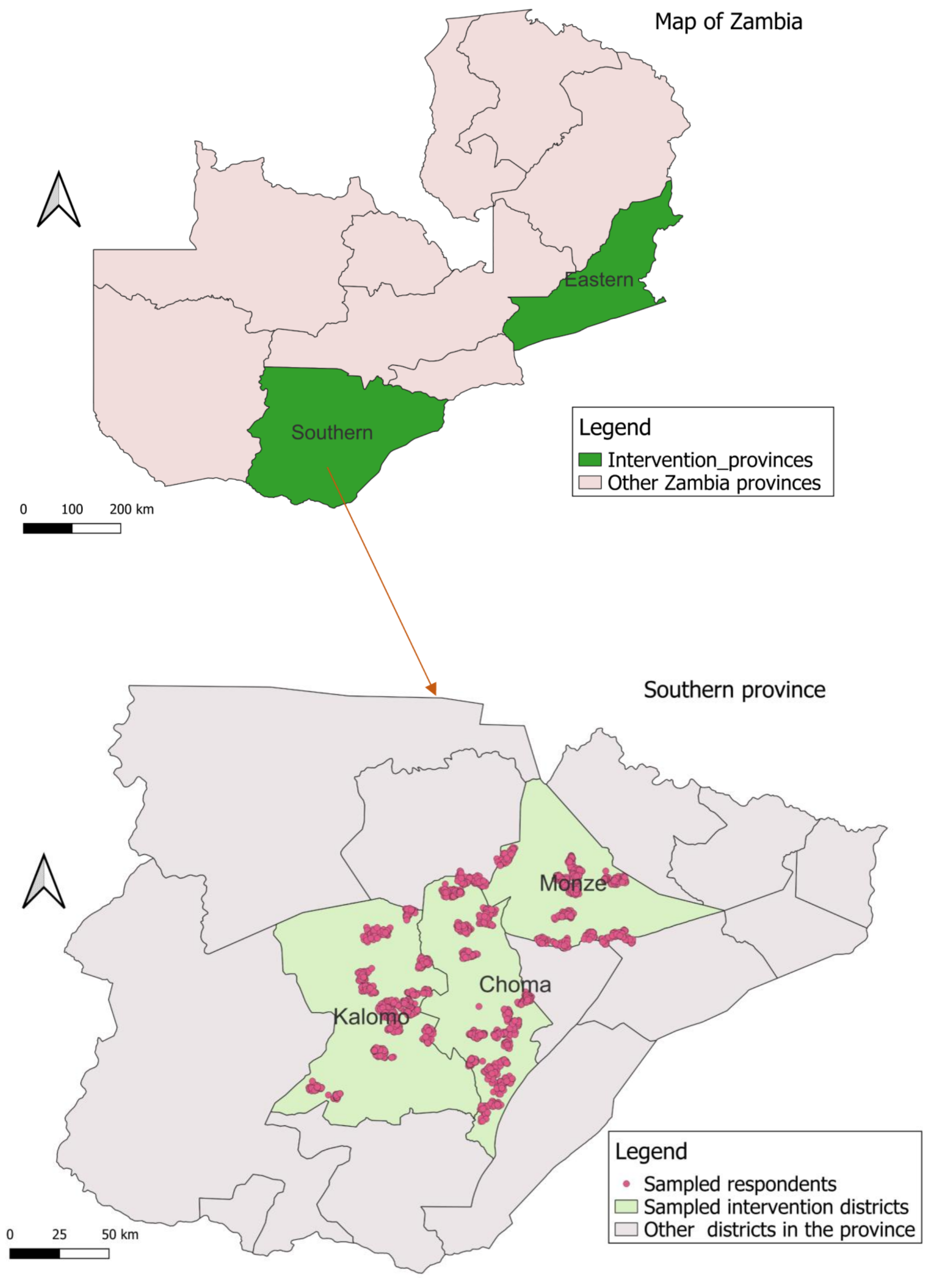

Figure 2: Study Area. The study was conducted in the Southern Province of Zambia

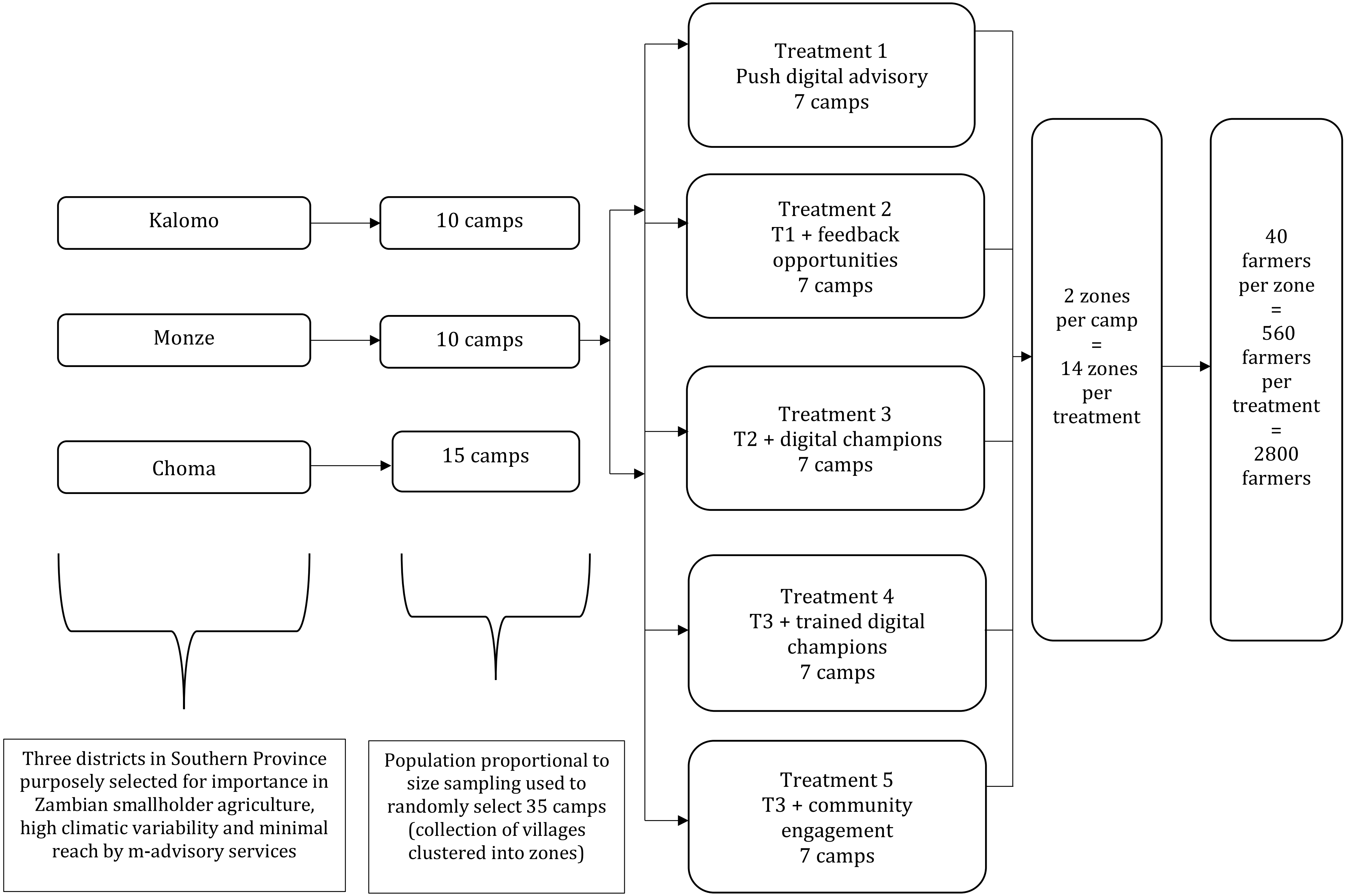

Figure 3: Study design

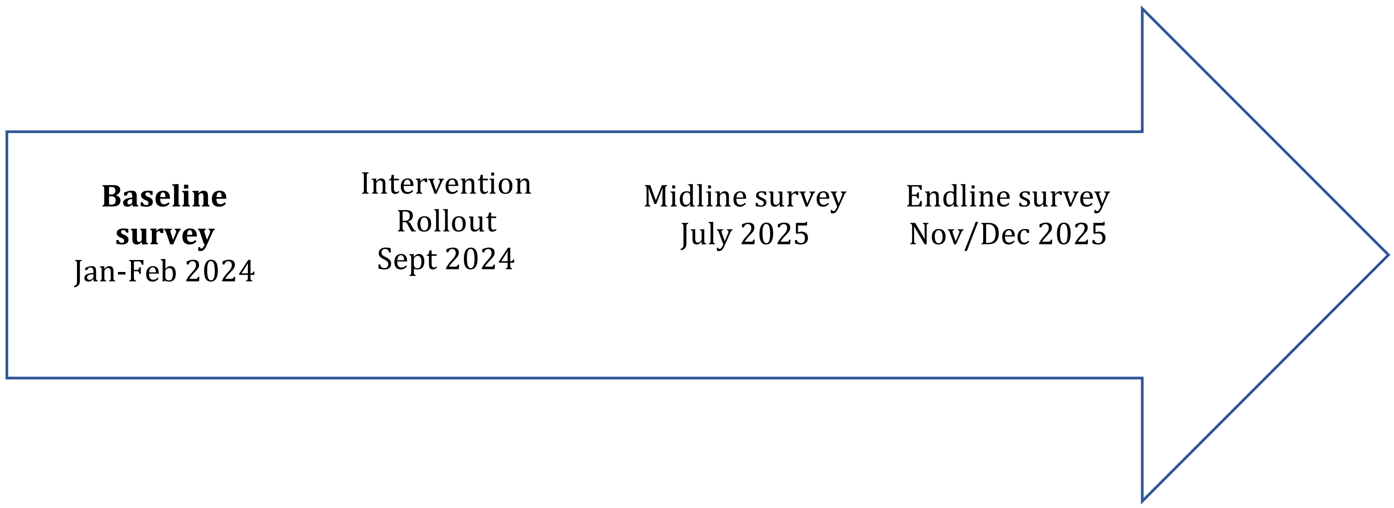

Figure 4: Project Timeline

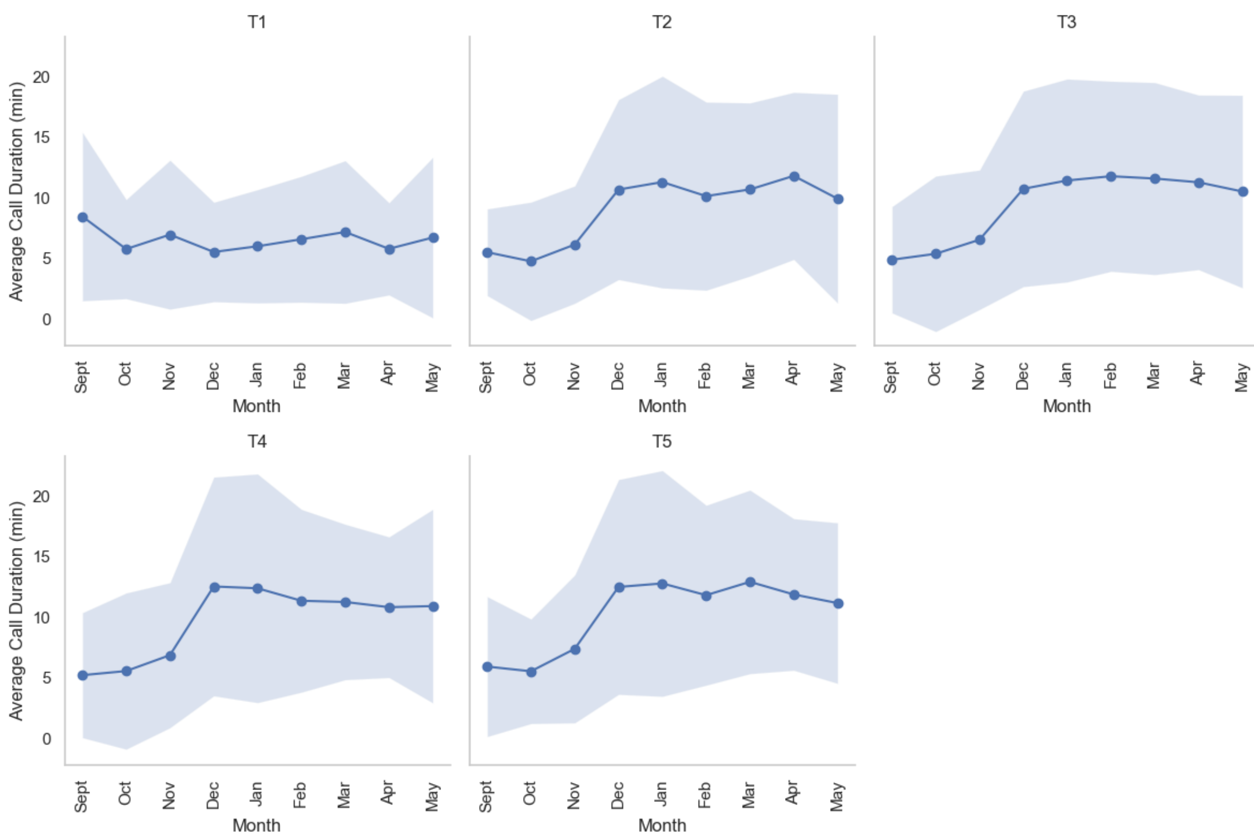

Fig 5: Average call duration by treatment group over time

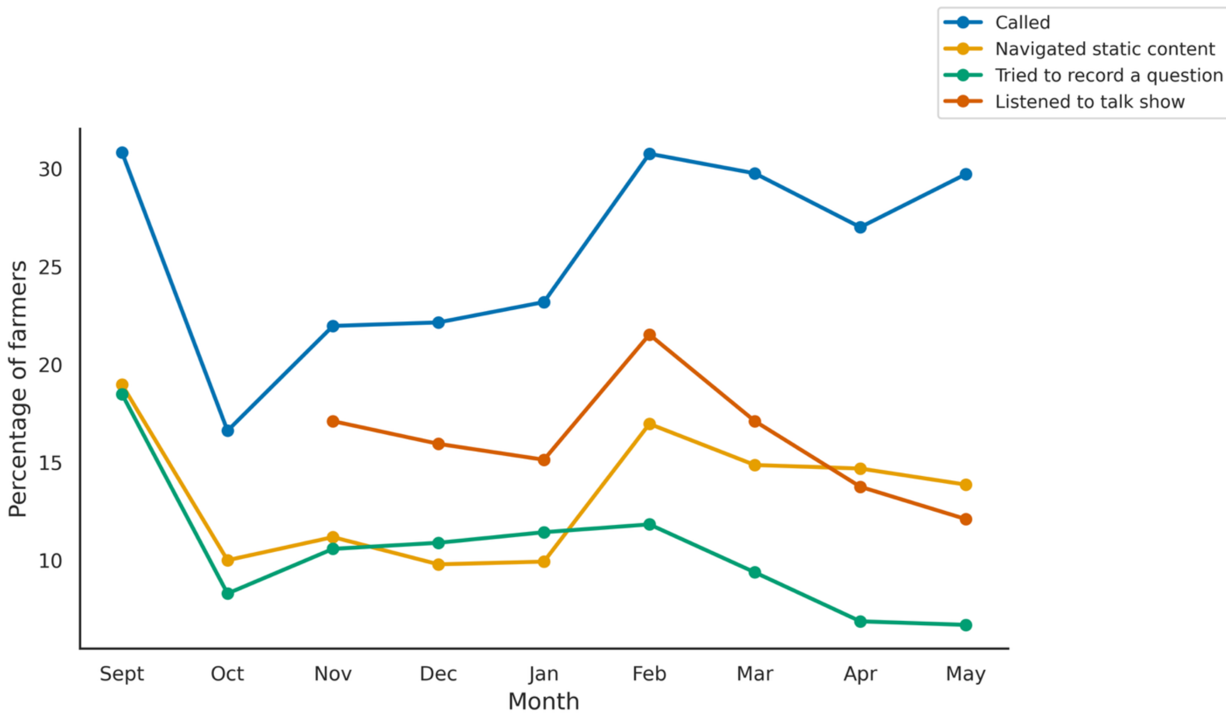

Figure 6: Trends in participation in the *Atubandike* platform by month; *Chi-square statistics indicate statistically significant differences in platform engagement across the months.*

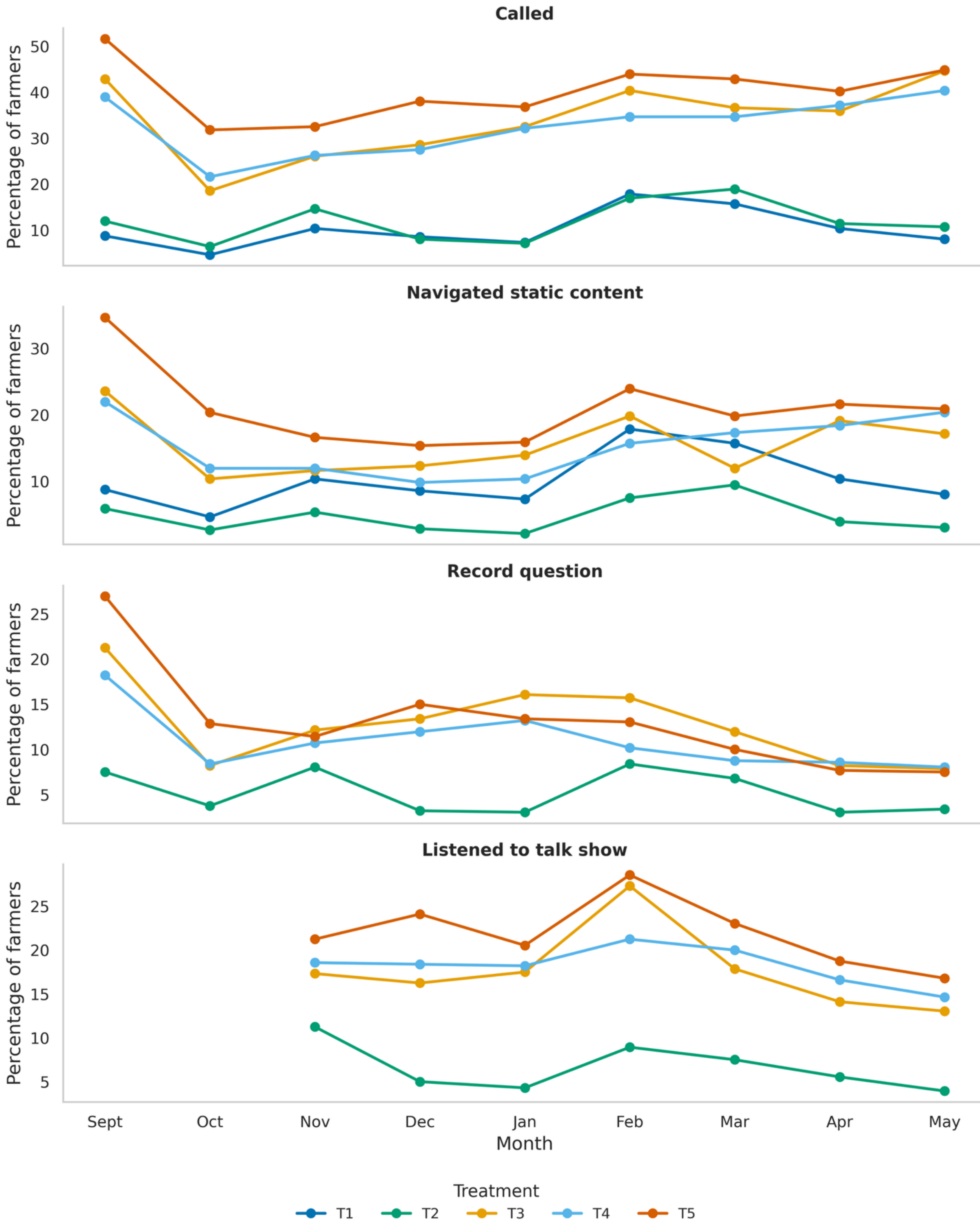

Figure 7: Trends in participation in the *Atubandike* platform by treatment group over time.

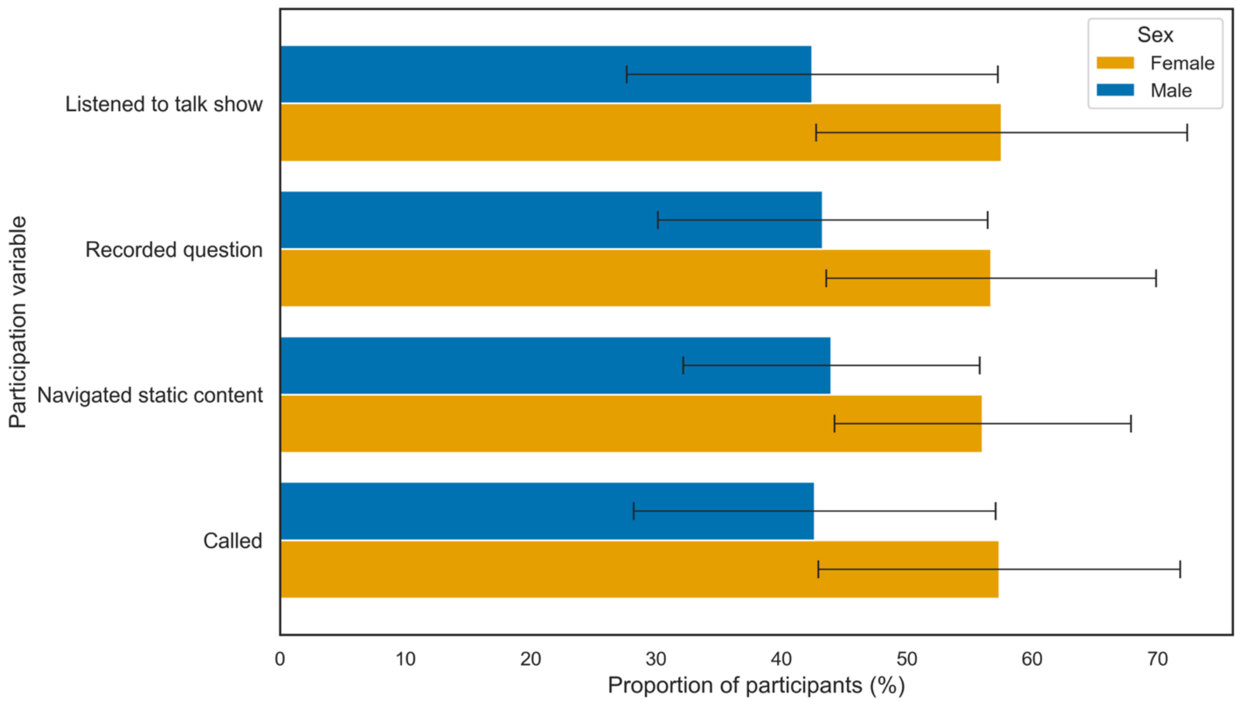

Figure 8: Participation in the Atubandike platform by sex

We considered using Oaxaca–Blinder decomposition to examine gender differences in digital advisory participation. Since our results indicated no significant gaps between men and women across most participation measures, we did not pursue this approach in the main analysis.

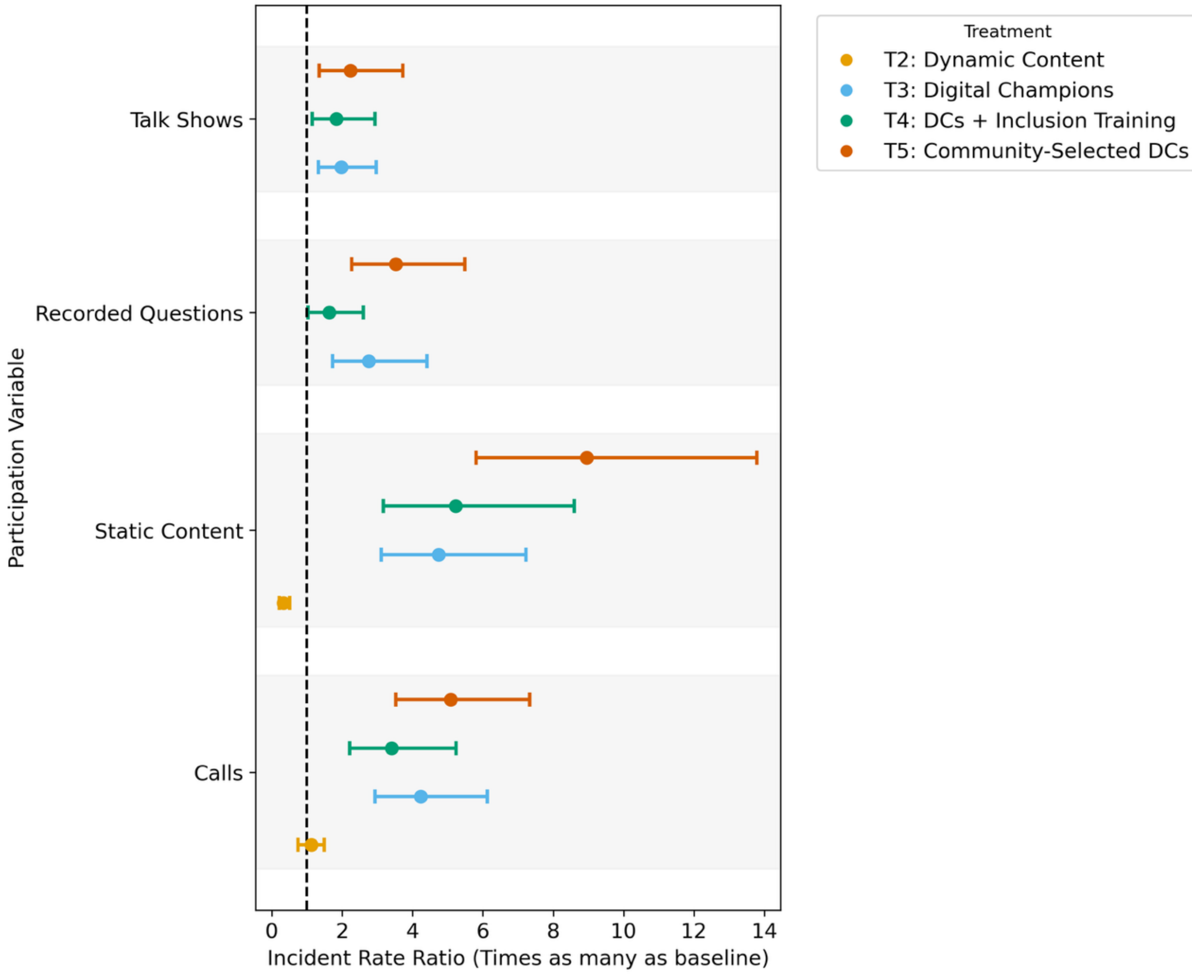

Figure 9: Incremental effects of digital interventions on farmer participation in the platform; Points show incidence rate ratios (IRRs) with 95% confidence intervals. The vertical line at 1 indicates no effect relative to the baseline. For calls, the IRR for T2 (dynamic content vs. static content) is not significantly different from 1. Across outcomes, digital champions (T3–T5) substantially increase participation, with the strongest effects observed for community-selected champions (T5).

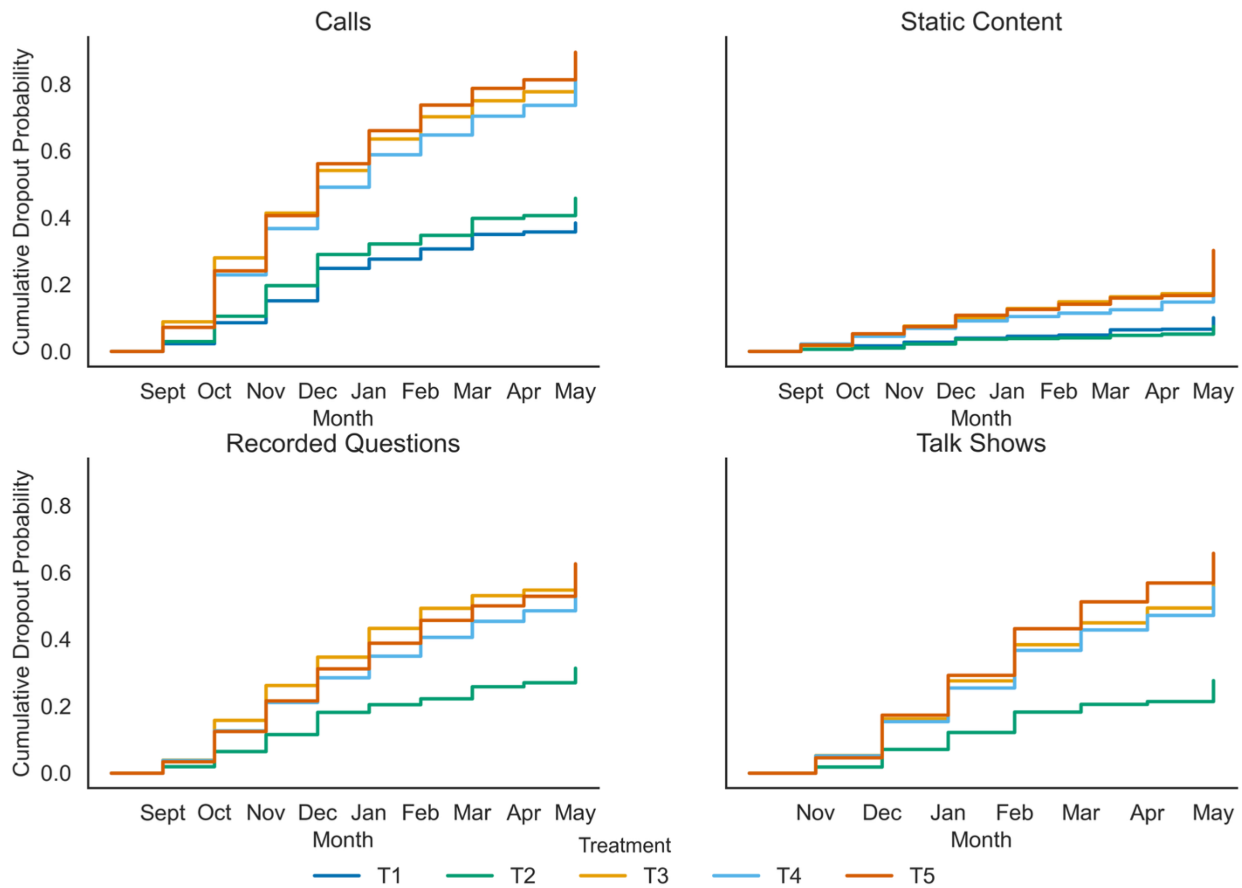

Figure 10: Cumulative dropout over time across four participation modes. Dropout curves are estimated using Kaplan–Meier methods. Treatments with digital champions (T3–T5) show higher early engagement and faster initial dropout, stabilizing later in the season. Static content users interacted less overall but showed steadier, more persistent engagement.

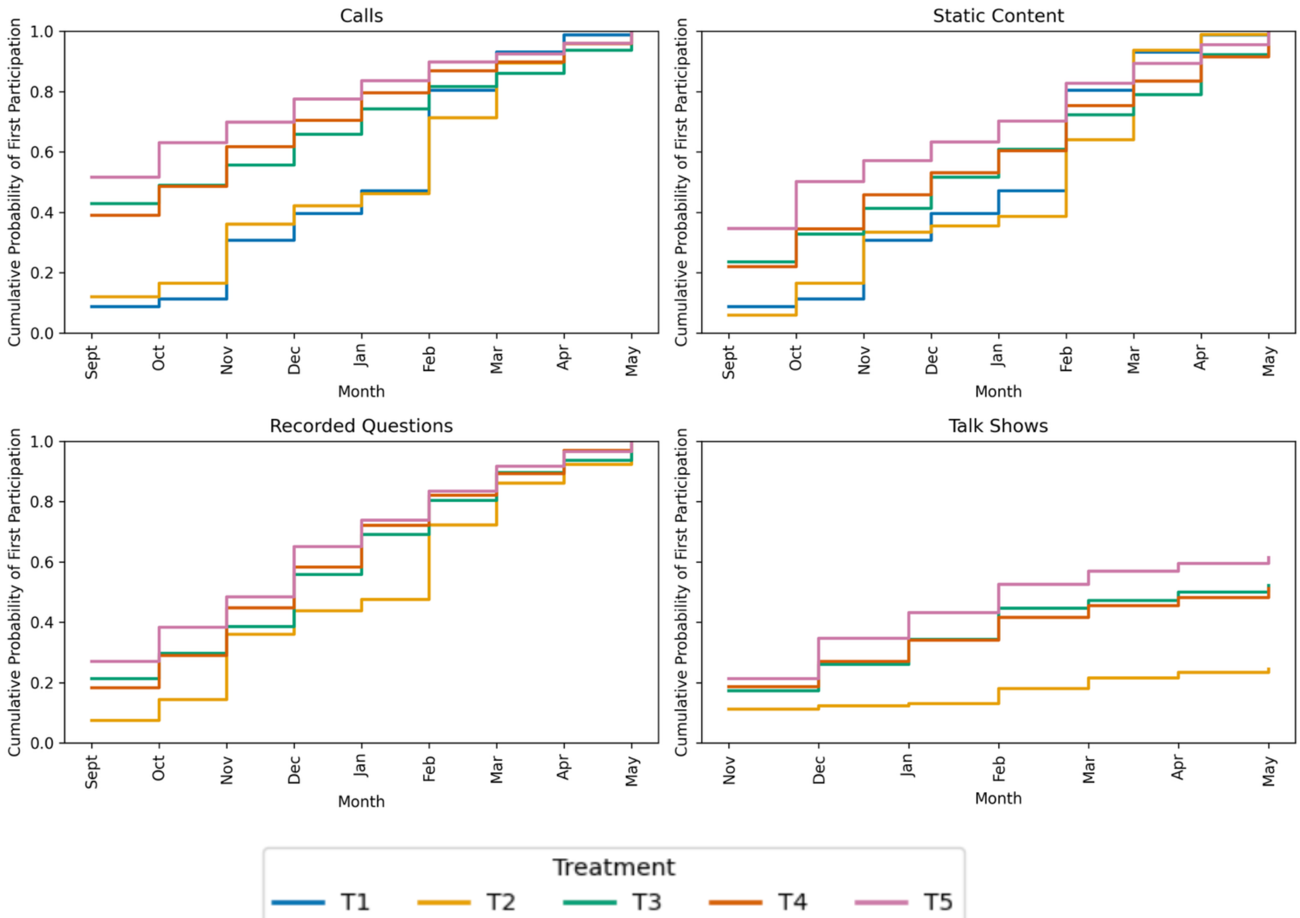

Figure 11: Cumulative first participation over time across four participation modes. Curves represent the cumulative share of farmers who engaged with the platform for the first time, estimated using Kaplan–Meier methods. Farmers in treatments with digital champions (T3–T5) reached their first participation substantially earlier than those in T1 and T2, indicating faster uptake and adoption of the service.

Appendix

Tables

Table A1: Proportion of farmers who participated in the digital advisory platform by month (%)

	Months										
Variable	**Sept**	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**	**April**	**May**	**Total**	**χ2 statistic**
Called	30.82	16.61	21.96	22.14	23.18	30.75	29.75	27.00	29.71	25.77	295.01***
Navigated static content	18.96	10.00	11.18	9.79	9.93	16.96	14.86	14.68	13.86	13.36	215.87***
Tried to record a question	18.48	8.30	10.58	10.89	11.43	11.83	9.38	6.88	6.70	10.50	238.93***
Listened to talk show	-	-	17.10	15.94	15.13	21.52	17.10	13.75	12.10	16.09	89.33***

Figures represent the proportion of the 2800 farmers who participated as described

Table A2: Proportion of farmers who participated in the digital advisory platform by month and treatment type (%)

	Months										
	Sept	Oct	Nov	Dec	Jan	Feb	Mar	April	May	Total	χ2 statistic
T1											
Navigated static content	8.75	4.64	10.36	8.57	7.32	17.86	15.71	10.36	8.04	10.18	84.34***
T2											
Called into platform	11.96	6.43	14.64	8.04	7.14	16.96	18.93	11.43	10.71	11.81	81.55***
Navigated static content	5.89	2.68	5.36	2.86	2.14	7.50	9.46	3.93	3.04	4.76	61.43***
Tried to record a question	7.50	3.75	8.04	3.21	3.04	8.39	6.79	3.04	3.39	5.24	50.44***
Listened to talk show	-	-	11.25	5.00	4.29	8.93	7.50	5.54	3.93	6.63	39.82***
T3											
Called into platform	42.86	18.57	26.07	28.57	32.50	40.36	36.61	35.89	44.64	34.01	143.51***
Navigated static content	23.57	10.36	11.61	12.32	13.93	19.82	11.96	19.11	17.14	15.54	70.93***
Tried to record a question	21.25	8.21	12.14	13.39	16.07	15.71	11.96	8.21	7.86	12.76	79.77***
Listened to talk show	-	-	17.32	16.25	17.50	27.32	17.86	14.11	13.04	17.63	49.95***
T4											
Called into platform	38.93	21.61	26.25	27.50	32.14	34.64	34.64	37.14	40.36	32.58	80.71***

Navigated static content	21.96	11.96	11.96	9.82	10.36	15.71	17.32	18.39	20.18	15.30	68.60***
Tried to record a question	18.21	8.39	10.71	11.96	13.21	10.18	8.75	8.57	8.04	10.89	49.08***
Listened to talk show	-	-	18.57	18.39	18.21	21.25	20.00	16.61	14.64	18.24	10.48
T5											
Called into platform	51.61	31.79	32.50	38.04	36.79	43.93	42.86	40.18	44.82	40.28	74.22***
Navigated static content	34.64	20.36	16.61	15.36	15.89	23.93	19.82	21.61	20.89	21.01	92.49***
Tried to record a question	26.96	12.86	11.43	15.00	13.39	13.04	10.00	7.68	7.50	13.10	132.43***
Listened to talk show	-	-	21.25	24.11	20.54	28.57	23.04	18.75	16.79	21.86	29.18***

Table A3: Proportion of farmers who recorded and shared experiences on the digital advisory platform by month and treatment type (%)

	Months										
	Sept	**Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**	**April**	**May**	**Total**	**χ2 statistic**
T2											
Recorded experience	2.68	1.07	2.68	0.71	0.00	0.71	2.86	1.07	0.71	1.39	36.71***
Listened to experience	-	-	5.36	3.21	2.14	4.46	6.61	3.57	1.07	3.78	32.88***
T3											
Recorded experience	6.61	2.32	4.46	2.50	4.82	3.75	3.57	2.68	2.32	3.67	26.27***
Listened to experience	-	-	10.36	9.29	10.89	11.96	14.64	12.32	13.21	11.81	10.54
T4											
Recorded experience	5.54	1.96	1.96	3.57	3.21	3.04	2.68	1.96	2.14	2.90	21.43***
Listened to experience	-	-	9.46	7.50	10.18	9.82	14.46	14.29	13.04	11.25	24.22***
T5											
Recorded experience	8.04	5.36	4.11	4.64	4.64	6.43	4.29	3.04	2.86	4.82	25.76***
Listened to experience	-	-	11.61	10.54	13.04	14.46	22.86	18.57	17.86	15.56	49.45***

Table A4: Mean call duration per participant by treatment and month

	Sept	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Total
T1	8.48 (6.96)	5.79 (4.10)	6.98 (6.15)	5.55 (4.11)	6.02 (4.68)	6.60 (5.20)	7.20 (5.89)	5.81 (3.81)	6.74 (6.63)	7.46 (1.00)
T2	5.53 (3.58)	4.78 (4.89)	6.16 (4.85)	10.70 (7.43)	11.32 (8.74)	10.16 (7.77)	10.71 (7.15)	11.83 (6.90)	9.95 (8.62)	9.45 (2.83)
T3	4.91 (4.39)	5.40 (6.42)	6.56 (5.76)	10.76 (8.07)	11.45 (8.38)	11.80 (7.85)	11.61 (7.93)	11.30 (7.21)	10.54 (7.95)	9.66 (2.86)
T4	5.24 (5.16)	5.58 (6.45)	6.89 (5.99)	12.56 (9.03)	12.41 (9.44)	11.38 (7.55)	11.28 (6.42)	10.85 (5.81)	10.94 (7.99)	10.02 (2.76)
T5	5.95 (5.78)	5.56 (4.32)	7.41 (6.11)	12.52 (8.87)	12.81 (9.32)	11.84 (7.43)	12.94 (7.58)	11.90 (6.26)	11.19 (6.63)	10.66 (2.73)
Total	6.49 (1.47)	6.01 (0.41)	7.41 (0.73)	11.07 (2.47)	11.48 (2.24)	10.20 (2.24)	11.09 (2.36)	10.72 (2.24)	10.57 (1.05)	9.45 (2.66)

The total average call duration for treatments and months is a weighted mean, calculated by dividing the total call duration by the total number of calls, rather than averaging the monthly means.

Table A5: Post-hoc Tukey Comparisons of Mean Call Duration by Treatment

Treatments	Difference in means	95% Confidence Interval
T2 vs T1	2.475 (0.450)	[1.247, 3.703]
T3 vs T1	2.937 (0.376)	[1.912, 3.963]
T4 vs T1	3.156 (0.378)	[2.125, 4.186]
T5 vs T1	3.620 (0.369)	[2.613, 4.627]
T3 vs T2	0.462 (0.355)	[–0.507, 1.432]
T4 vs T2	0.680 (0.357)	[–0.295, 1.655]
T5 vs T2	1.145 (0.348)	[0.195, 2.095]
T4 vs T3	0.218 (0.258)	[–0.486, 0.922]
T5 vs T3	0.683 (0.245)	[0.014, 1.351]
T5 vs T4	0.465 (0.248)	[–0.212, 1.141]

The table reports mean differences in average call duration (minutes per call) between treatment groups, based on Tukey's Honest Significant Difference test. Confidence intervals that do not include zero indicate statistically significant differences at the 5% level. Standard errors in parentheses.

Table A6: Random-effects Poisson regression results of participation against treatment (base=T2)

	Called	Navigated static content
	Treatments (base: T2)	
T1	0.893 (0.163)	2.974*** (0.764)
T3	4.236*** (0.798)	4.741*** (1.020)
T4	3.408*** (0.748)	5.227*** (1.328)
T5	5.085*** (0.951)	8.946*** (1.974)
Months (base: Sept)		
Oct	0.581*** (0.067)	0.720*** (0.269)
Nov	1.521*** (0.117)	1.494** (0.304)
Dec	0.671** (0.128)	0.440*** (0.114)
Jan	0.479*** (0.105)	0.226*** (0.093)
Feb	1.335* (0.198)	0.935 (0.205)
Mar	1.659 (0.633)	2.494** (1.090)
Apr	0.844 (0.253)	0.994 (0.405)
May	0.880 (0.347)	0.357 (0.231)
Districts (base: Choma)		
Kalomo	0.967 (0.023)	0.972 (0.026)
Monze	1.770*** (0.120)	1.849*** (0.078)
Treat*month	Included	Included
Constant	0.228*** (0.039)	0.214*** (0.042)
Number of observations	25 200	25 200

*The regression includes all treatment-by-month interactions (Treat × Month). Coefficients for these interactions are not shown individually in this table for brevity. Coefficients represent the incident rate ratios (IRRs); The IRR relative to T2 is the inverse of the IRR relative to T1. Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1*

Table A7: Random-effects Poisson regression results of participation against treatment - with socioeconomic control variables

	Calls	Navigations of static content	Recorded questions	Talk shows listened to
	Treatments (base: T1)		*Treatments (base: T2)*	
T2	1.095 (0.362)	0.299 (0.941)		
T3	4.878*** (2.181)	1.564 (3.508)	2.943** (1.338)	1.967 (0.873)
T4	3.993*** (2.114)	1.758 (5.638)	1.720 (0.749)	1.879 (0.998)
T5	5.848*** (0.674)	2.991 (0.580)	3.628*** (1.406)	2.307* (1.054)
Months (base: Sept)			*Months (base: Nov)*	
Oct	0.592*** (0.117)	0.443*** (0.080)	0.263*** (0.063)	
Nov	1.075 (0.115)	0.977 (0.081)	0.575*** (0.119)	
Dec	0.912 (0.118)	0.755** (0.101)	0.240*** (0.057)	0.466*** (0.095)
Jan	0.748* (0.124)	0.709 (0.311)	0.144*** (0.056)	0.313*** (0.072)
Feb	2.088*** (0.324)	1.734** (0.448)	0.575* (0.191)	0.649*** (0.091)
Mar	2.048*** (0.195)	1.767*** (0.367)	0.557 (0.330)	0.710* (0.144)
Apr	1.130 (0.172)	0.948 (0.149)	0.251*** (0.092)	0.374*** (0.090)
May	0.844 (0.119)	0.905 (0.330)	0.234*** (0.121)	0.313*** (0.133)
Districts (base: Choma)				
Kalomo	0.960 (0.240)	0.924 (1.253)	1.036 (0.228)	0.967 (0247)
Monze	1.684** (0.419)	1.743*** (0.078)	1.301 (0.515)	1.569* (0.371)
Age	0.995 (0.034)	0.983 (0.132)	1.002 (0.029)	0.999 (0.030)
Male	0.922 (0.884)	0.925 (3.542)	0.915 (0.570)	0.933 (0.786)
Household size	0.985 (0.129)	1.000 (0.606)	0.980 (0.126)	0.986 (0.091)
Years lived in zone	1.000 (0.027)	1.002 (0.117)	1.000 (0.028)	0.998 (0.022)

Income sufficiency				
Allows to save a little	1.381 (2.799)	1.072 (9.753)	1.383 (2.189)	1.256 (2.315)
Only meets expenses	1.542 (2.827)	1.118 (8.812)	1.279 (1.892)	1.405 (2.708)
Not sufficient	1.550 (3.476)	1.450 (17.135)	1.369 (2.383)	1.400 (2.859)
Really not sufficient (have to borrow)	1.557 (3.685)	1.319 (14.682)	1.319 (2.021)	1.309 (2.008)
Education level				
None	1.007 (1.797)	1.021 (9.015)	0.760 (1.570)	1.090 (2.163)
Upper Primary	1.010 (1.205)	1.134 (5.383)	1.185 (1.125)	1.089 (0.914)
Junior Secondary	1.043 (1.520)	1.206 (9.428)	0.976 (1.107)	1.139 (1.516)
Senior Secondary	0.952 (1.012)	1.091 (6.193)	0.744 (0.727)	0.827 (0.910)
Trade Certificate	2.582 (22.843)	1.967 (64.911)	2.794 (17.330)	3.942 (43.170)
Tertiary	0.426 (0.749)	0.545 (5.565)	0.416 (0.510)	0.438 (0.641)
Marital Status				
Married (monogamous)	1.036 (1.094)	1.167 (4.284)	1.060 (0.921)	0.958 (0.641)
Married (polygamous)	0.952 (1.626)	1.115 (8.729)	1.051 (1.089)	1.101 (1.792)
Cohabiting	1.547 (10.134)	2.540 (65.280)	0.148 (0.300)	2.244 (9.037)
Widowed	0.766 (1.384)	1.028 (8.780)	0.798 (1.117)	0.750 (1.205)
Divorced	0.811 (2.015)	0.830 (6.183)	0.975 (1.430)	0.956 (1.475)
Separated	0.744 (1.989)	0.784 (6.605)	0.442 (0.725)	0.727 (1.913)
Land area (ha)	0.986 (0.089)	0.979 (0.434	0.992 (0.100)	0.977 (0.080)
Received advice through phone	0.946 (0.876)	1.091 (5.995)	1.091 (0.801)	0.989 (0.901)
Credit source				
NGO	0.919 (1.877)	1.050 (10.530)	1.178 (2.725)	0.499 (0.817)
Formal lender (e.g. bank)	1.201 (3.136)	1.294 (10.200)	1.203 (2.204)	1.162 (2.764)
Informal lender	0.980 (1.754)	0.974 (8.935)	1.246 (1.976)	1.018 (1.740)

Friends/relatives	1.120 (1.409)	1.315 (6.233)	1.240 (1.306)	1.092 (1.671)
Group-based microfinance	1.196 (2.097)	1.146 (7.400)	1.316 (1.600)	0.941 (1.633)
Traders	1.077 (4.880)	1.235 (14.730)	1.386 (3.978)	1.126 (4.615)
None	0.936 (1.592)	1.120 (6.775)	1.072 (1.338)	0.820 (1.416)
Crops grown				
Soybean	1.026 (0.994)	1.001 (4.110)	1.097 (0.751)	0.921 (0.568)
Groundnut	1.074 (0.810)	1.248 (5.599)	0.998 (0.724)	1.508 (0.972)
Keep livestock	1.326 (2.325)	1.223 (11.910)	1.404 (1.816)	1.283 (2.118)
Owns phone	0.113 (0.435)	1.270 (3.618)	1.172 (1.294)	1.411 (0.868)
Treat*month	Included	Included	Included	Included
Constant	0.113 (0.435)	0.431 (7.693)	0.110 (0.327)	0.078 (0.306)
Number of observations	25 200	25 200	20 160	15 680

Figures

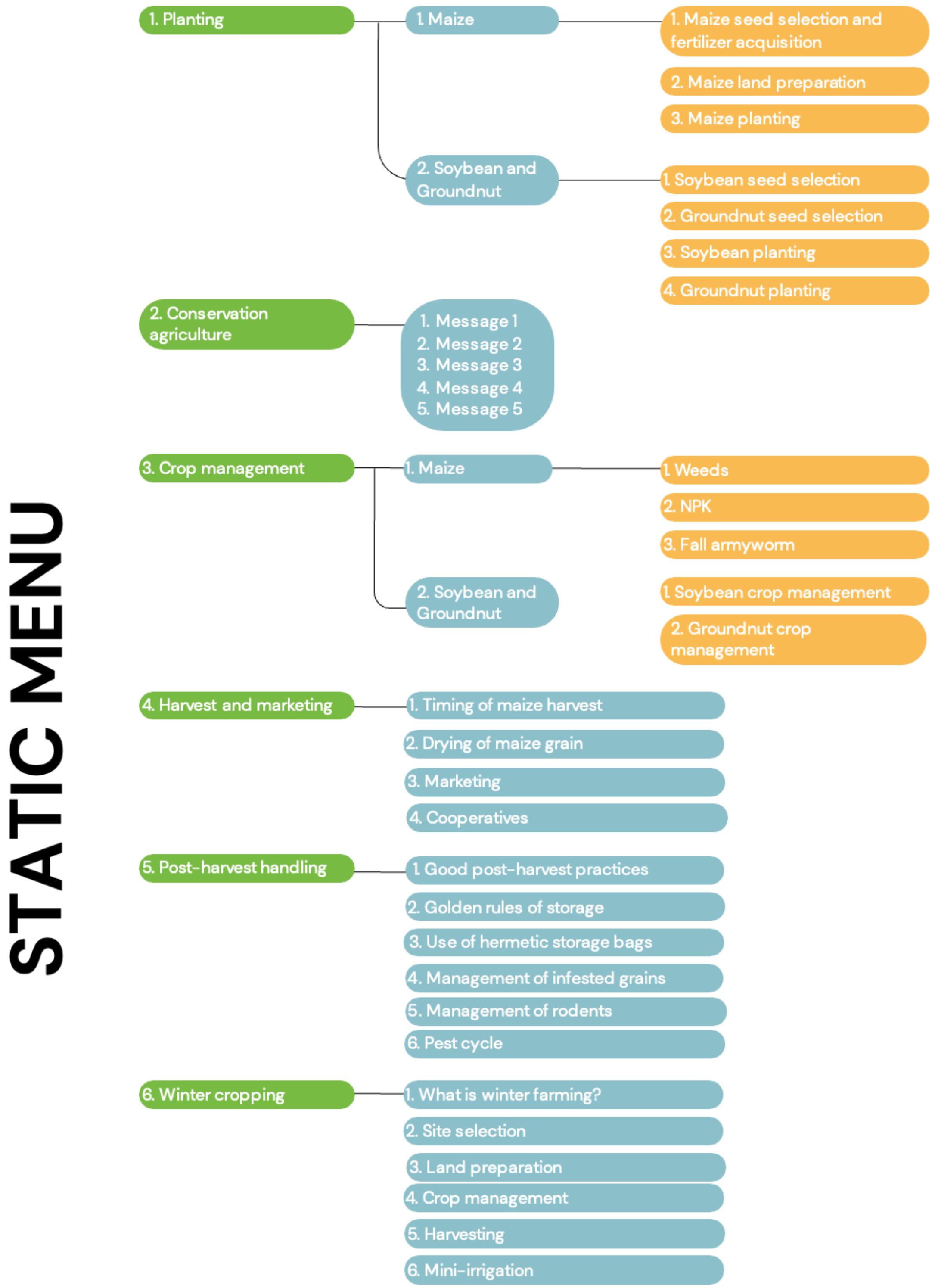

Figure A1: *Atubandike* content menu

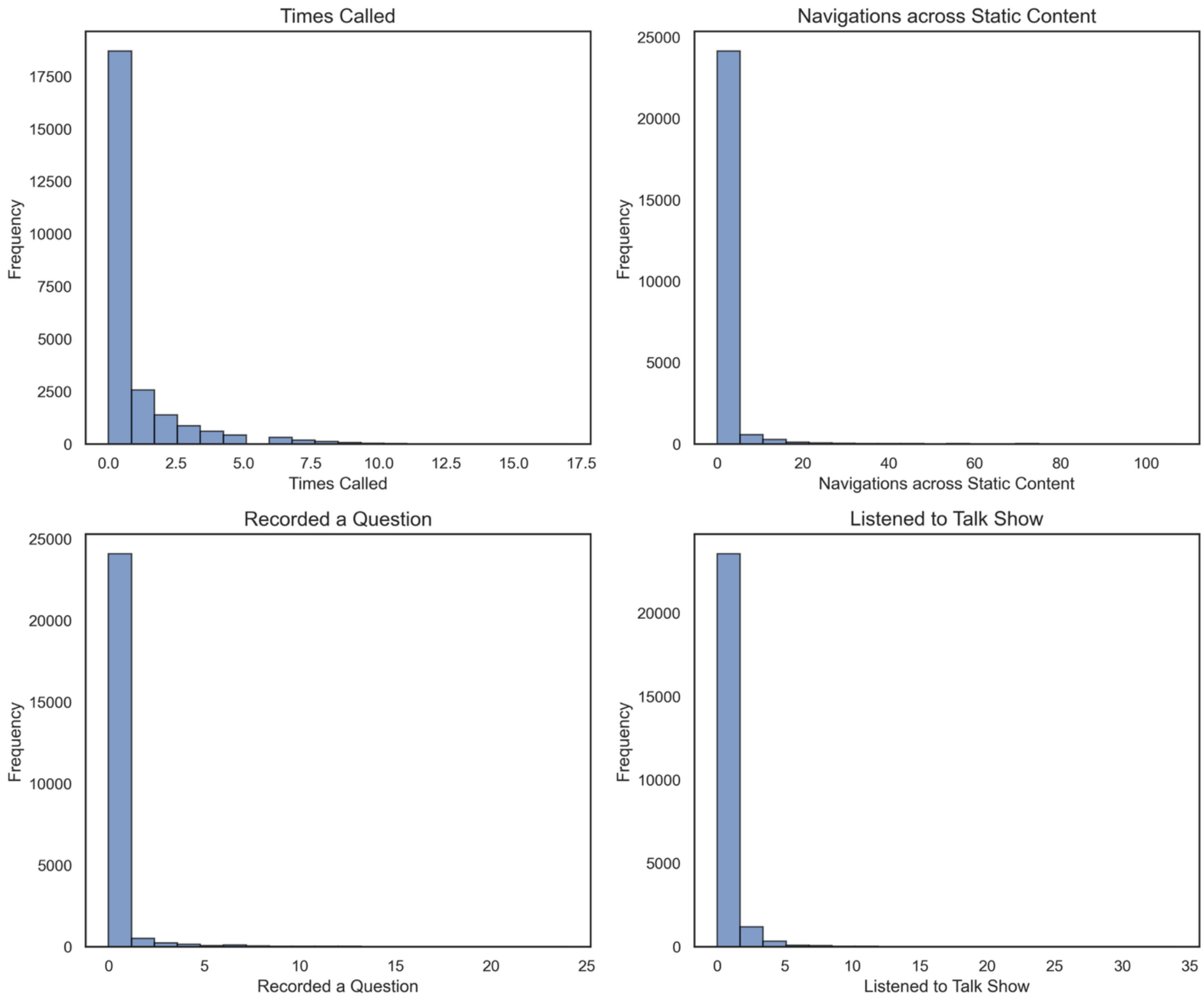

Figure A2: Distribution of participation variables