Impact of Text Messages on Farmers' Adoption of Agriculture App and Its Effect on Farm Level Outcomes

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Abstract

Smartphones and Mobile phone applications (MPAs) are increasingly promoted as cost-effective tools to improve agricultural decision-making and farm outcomes in developing countries. However, adoption of such digital technologies remains limited. This study evaluates the behavioral impact of periodic text reminders on adoption of a smartphone-based MPA and assesses the MPA's subsequent effects on farm-level outcomes. We conducted a randomised controlled trial (RCT) with 1,006 farmers in rural India, where half the participants received text message nudges encouraging them to use MPA. The reminders significantly increased adoption, as measured by app installation and login activity, though they did not affect the total time spent on MPA. Using an instrumental variable approach, we estimate the causal impact of MPA use on two farm outcomes: prices received for crop output and expenditure on inputs (pesticides and fertilisers). We find that greater engagement with MPA leads to higher output prices and lower input costs, suggesting improvements in market access and input-use efficiency. These results demonstrate how low-cost behavioral interventions, such as SMS nudges, can support diffusion and effective use of digital tools in agriculture. The findings offer actionable insights for policy initiatives aimed at enhancing agriculture productivity and efficiency through behavioural and technological innovations.

Keywords: Text messages, Mobile Phone Application, Smartphone, Price realisation, Input expenditure.

Impact of Text Messages on Farmers' Adoption of Agriculture Mobile Phone Application and Its Effect on Farm Input Use and Crop Prices

1. Introduction

Farm information plays a crucial role in improving agricultural productivity and farmer livelihoods. The farmers worldwide increasingly demand timely, reliable, and accurate agricultural information. In many developing countries, the traditional government agricultural extension services are ineffective in providing credible information to the farmers due to poor planning and execution, manpower shortage, low cost-effectiveness, and lack of accountability (Ali & Kumar, 2011; Dalwai, 2017; Glendenning et al., 2010; Glendenning & Ficarelli, 2012). The growing use of smartphones offers a potential alternative channel for delivering agricultural information to farmers at minimal cost (Aker, 2011). A host of smartphone-based Mobile Phone Applications (MPAs) now provide farmers with information on the critical aspects of farming, such as weather and market conditions, commodity prices, input usage, crop selection, and crop management (Dossani et al., 2005; Brugger, 2011; Premachandra & Kumara, 2021). The MPAs also enable farmers to interact directly with several agricultural value chain players, such as traders, suppliers, and extension officers (Duncombe, 2016).

Despite increasing mobile phone ownership, the uptake of MPAs among farmers remains very low in developing and emerging economies. For instance, only about 0.8% to 1.2% of Indian farming households received technical advice using MPAs from June-December 2018 to January-June 2019 (Jadhav, 2022). NASSCOM (2021) estimates that only 2% of Indian farmers use MPAs in their farming activities. The limited use of agricultural technologies, such as MPAs, may be due to informational market inefficiencies: many farmers are either unaware of the technology's existence or unconvinced of its potential benefits (Van Campenhout et al. 2017). In such situations, a key challenge for policymakers is to induce behavioural changes among farmers to encourage technology adoption (Larochelle et al. 2019). Reminders can help overcome farmers' inertia toward newer technology by informing them about its benefits and reducing information asymmetry (Dong & Saha, 1998). Studies have shown that low-cost interventions, such as reminder text messages, have encouraged the adoption of improved agricultural practices and inputs (Carrión-Yaguana et al., 2020; Giulivi et al., 2023). Text messages are particularly attractive as an outreach tool because they are inexpensive, scalable, and can be saved and referenced later by farmers.

Another concern related to digital agriculture technologies is whether they can measurably improve farm outcomes such as crop yields, input use efficiency, incomes, and market prices. Prior research has shown that greater access to information through Information and Communication Technology (ICT) interventions, such as mobile phone services, can increase farm productivity and household welfare (Aker, 2011; Martin & Hall, 2011; Minten & Barrett, 2008). Mobile phone-based information services – including SMS price alerts and helpline services – have been found to change farmer behavior and result in gains in income or price realisation in various countries (Muto & Yamano, 2009; Fafchamps & Minten, 2012; Tadesse & Bahiigwa, 2015). However, there is little empirical evidence on the impact of smartphone applications on smallholders' economic outcomes, especially in South Asia. Barring Fafchamps & Minten (2012), the impact of informational services provided to farmers in India on their welfare has largely gone unexamined.

The objective of this paper is two-fold: First, using a Randomised Control Trials (RCT) design, it aims to examine the impact of an intervention in the form of mobile phone-based text messages/reminders (hereafter "text messages") in encouraging Indian farmers to adopt and use MPA for conducting farming activities. These text messages specifically target behavioral frictions such as inertia, limited attention, and present bias that often impede farmers' adoption of digital agricultural tools beneficial to them. Second, it examines the impact of MPA-provided information services on the prices realised and the expenditure incurred on pesticides and fertilisers by Indian farmers. These two aspects of agriculture technology adoption have not been adequately studied in the Indian context. Among various communication-based reminders, text messages are among the most cost-effective and easily implemented tools for encouraging behavioural change among farmers.

The rationale for using reminder-based nudges draws directly from behavioral economics and the framework of 'libertarian paternalism' (Thaler & Sunstein 2003; Thaler & Sunstein 2008). Even when farmers value new technologies, adoption is often hindered by some behavioral frictions. First, there is limited attention and cognitive load (Gabaix 2019). These are common in settings where farmers manage multiple tasks daily, which reduces the likelihood of consistent engagement with a new digital tool after initial exposure. Second, present bias and procrastination lead individuals to postpone learning unfamiliar technologies, especially when the perceived benefits are delayed or uncertain (DellaVigna & Malmendier, 2006). Third is the status quo bias and inertia that favour existing practices (Dong & Saha, 1998), leading farmers to defer the effort required to incorporate app-based information into their routines.

These behavioral frictions were evident in our baseline interactions, where many farmers expressed interest in the MPA but reported forgetting about it or lacking the immediate mental bandwidth to experiment with it. In this context, periodic SMS/text reminders or messages function as non-coercive prompts that bring the app back to the top of farmers' attention (Karlan et al. 2016; Carrión-Yaguana et al. 2020) at moments aligned with the cropping cycle. The reminders reduce the cognitive effort required to remember and initiate action, encouraging engagement. Text messages are accessible to even basic mobile phone users and allow farmers to retain information for later reference or sharing (Mittal & Mehar, 2016; Larochelle et al., 2019). This behavioral rationale makes reminder-based nudges particularly suitable for our study setting, where informational interventions alone may be insufficient to overcome attention-related and psychological barriers to sustained digital technology use. At the policy level, text messages are more relevant for India, as they can be targeted and delivered easily through the existing government machinery.

This study contributes to the existing literature on RCTs in digital agriculture in a few unique ways. This is the first study in South Asia to employ randomised text reminders to encourage the installation of an MPA and to estimate the impact of its use on farm-level metrics causally. Unlike most prior studies on agricultural digital interventions, which infer technology adoption's impact from self-reported outcomes or focus on basic SMS advisory, we directly measure engagement and economic outcomes for an MPA, moving beyond mere access to actual behavioural change. The findings of this study provide scalable and cost-effective strategies for policymakers seeking to move beyond traditional extension and unlock the productive potential of digital platforms for marginalised farming populations. This is one of the first RCTs in India to examine both technology adoption and price/income effects of MPA usage.

The rest of the paper is organised as follows. Section 2 reviews related literature on interventions to encourage agricultural technology adoption and the impacts of technology adoption on farm outcomes. Section 3 describes the study context, experimental design, data collection, and empirical methodology. Section 4 presents and discusses the results of the empirical analysis. The last section concludes with policy implications and suggestions for further research.

2. Literature Review

Researchers have explored various strategies to increase the adoption of agricultural technologies in developing countries. One strand of the literature uses RCTs to test interventions that nudge farmers toward adopting new technologies. These interventions include leveraging social networks, extension services, financial incentives, text messages, and video-based extension services. The impact of these interventions has been mixed, depending on the type of technology, local context, and mode of delivery. Social network-based interventions such as training or incentivising peer farmers, have had some success in diffusing new farm practices but are often complex to implement (Beaman et al., 2021; BenYishay & Mobarak, 2018). In Malawi, studies by BenYishay and Mobarak (2018) and Beaman et al. (2021) found that peer influence and targeted social network interventions played a significant role in encouraging the adoption of techniques such as pit planting and Chinese composting. These studies suggest that learning from fellow farmers can be more effective than conventional extension approaches. However, not all social interventions yielded success. A recent study by Okello et al. (2023) in Uganda found that using social incentives to promote the adoption of improved sweet potato varieties had no measurable impact.

Pamuk et al. (2014) demonstrate that engaging local stakeholders in identifying and solving agricultural problems resulted in higher adoption of crop management practices across several African countries. The use of ICT tools for agricultural advice has been explored in several studies, with mixed results. In Ecuador, Larochelle et al. (2019) showed that farmers who received SMS messages about integrated pest management (IPM) were more likely to adopt those practices. However, Cole and Fernando (2018), in their study from India, observed that while ICT advisory services altered farmers' information sources and certain farming practices, they did not lead to measurable improvements in yield or profitability, suggesting limitations in translating information access into productivity gains. Giulivi et al. (2023) found that smartphone apps and extension training increase the adoption of improved fertiliser practices by 8.4 and 13 percentage points, respectively, among Nepalese farmers. Financial interventions, particularly through microcredit, have produced nuanced findings. Nakano and Magezi (2020), studying farmers in Tanzania, noted that access to credit did not affect fertiliser use among farmers with good irrigation access, likely because these farmers were already using fertiliser optimally. However, for farmers with limited irrigation and low prior fertiliser use, credit access did increase fertiliser adoption, highlighting the differentiated impacts of financial tools.

To the best of our knowledge, only three studies (Casaburi et al., 2014; Giulivi et al., 2023; Larochelle et al., 2019) have used text message-based interventions in agriculture technology adoption literature, though no study has investigated the role of text messages/reminders in the adoption of agriculture MPA in South Asia. Many studies have examined the impact of agricultural technology adoption, such as high-yielding seeds, information and communication technologies (e.g., internet connectivity and mobile phones), and improved storage, on farm outcomes, including some in India (e.g., Ali and Kumar, 2011; Fafchamps and Minton, 2012; Cole and Fernando, 2018). For instance, Minten and Barrett (2008) found that the introduction of high-yielding varieties in Madagascar led to significant gains in agricultural productivity, resulting in lower food prices and increased real wages for unskilled workers. Similarly, Becerril and Abdulai (2010) reported that the adoption of improved maize varieties in Mexico was associated with higher per capita expenditure and reduced poverty.

Ali and Kumar (2011) assessed India's e-Choupal initiative and found it enhanced farmers' decision-making abilities. Muto and Yamano (2009) observed that mobile phone coverage in Uganda led to increased banana sales in remote areas, though this effect was not observed for maise. Similar trends were identified in the Philippines, where Lee and Bellemare (2013) found that mobile phone ownership led to a 5–8% increase in the prices farmers received. On the other hand, Tadesse and Bahiigwa (2015) found no significant impact of mobile phone ownership on market selection or price realisation in Ethiopia, suggesting possible limits of ICT in contexts where complementary infrastructure or market access is weak. Cole and Fernando (2018) observed that ICT-based advisory services changed cotton and cumin farming practices in India, though the effect on yields was modest. SMS-based advisory services have demonstrated mixed but often positive results. In India, Fafchamps and Minten (2012) showed that farmers receiving SMS information improved their market engagement through spatial arbitrage and better crop grading. In Kenya, Casaburi et al. (2014) found that SMS messages containing fertiliser advice increased yields by 11.5%. Similar ICT-based market information services in Kenya also positively influenced input use and labour productivity, according to Ogutu et al. (2014).

Mason and Smale (2013) also showed that the adoption of hybrid maize seed in Zambia improved smallholder well-being. In Nigeria, Afolami et al. (2015) reported increased income and consumption from improved cassava varieties, while Awotide et al. (2013) found that a seed voucher program significantly raised household income and consumption. Omotilewa et al. (2018) found that the provision of improved storage technology in Uganda increased the likelihood of planting hybrid maize by 10 percentage points. More recent work has examined bundled or multi-component technology interventions. Khonje et al. (2018) in Zambia demonstrated that adopting a suite of agricultural technologies, rather than individual components, resulted in stronger impacts on yields, income, and poverty reduction. Despite the wide array of studies examining the impact of agricultural technology adoption, studies exploring the impact of smartphone-based MPA on agricultural outcomes remain limited.

Beyond technological and informational constraints, a growing body of research has emphasised the role of behavioral frictions in shaping farmers' adoption of new technologies. Limited attention and cognitive load (Gabaix, 2019; DellaVigna, 2009), present bias and procrastination (O'Donoghue & Rabin, 1999; DellaVigna & Malmendier, 2006), and status quo bias or behavioral inertia (Samuelson & Zeckhauser, 1988; Dong & Saha, 1998) can all delay farmers' adoption of technology. Evidence from agricultural settings indicates that farmers often forget about or postpone using new information services after initial exposure (Larochelle et al., 2019; Cole & Fernando, 2018). Reminder-based nudges have been shown to effectively counteract these attention-related barriers by bringing intended actions "top of mind" at relevant moments (Karlan et al., 2016; Carrión-Yaguana et al., 2020).

3. Methodology

3.1 Study Area and Experimental Design

We conducted a field experiment in Pulivendula Mandal, Kadapa district, Andhra Pradesh, India, where agriculture is the primary livelihood for about 80% of households. Semi-arid conditions and a mix of crops, including groundnut, sunflower, turmeric, cotton, and Bengal gram, characterise the study area. With assistance from local authorities, we selected 14 villages in this Mandal with similar agroecological conditions (soil type and climate) and cropping patterns to ensure a fairly homogeneous setting for the trial. Within these villages, we obtained official lists of farmers and applied eligibility criteria to identify our sample: we included individuals whose primary occupation was farming and who had cultivated crops in the past two seasons. This yielded a baseline sample of 1,006 farming households.

[Insert Figure 1 here]

All sample farmers were introduced to the mobile application "Na Panta" at the start of the study (Figure 1). *Na Panta* is a smartphone app available in Telugu, the local language, that provides a comprehensive suite of agricultural information and services. These include features on soil testing, crop management practices, pest and disease identification, weather forecasts, market prices, locations of input dealers and cold storage facilities, government agricultural schemes, and an agriculture news forum[1]. As the app's information is sourced from agricultural universities and government databases, it was considered reliable and locally relevant. There were no monetary costs for farmers to install or use the NaPanta app. The app was free to download and use, with no carrier charges or paywalls for accessing its content. The NaPanta app provided crop-specific agronomic recommendations. At registration, farmers indicated the crops they were growing (along with acreage), and the app automatically tailored the advisories to those crops. We verified that the MPA module contained information for all crops cultivated in the study area during the experiment period, ensuring full coverage. Since crop information

[1] Prior to conducting RCT, we conducted an exploratory study in the study region. More than 50 percent of farmers covered in the exploratory study had access to smartphones. In addition to smartphone, MPA could be downloaded in Jio phones as well. Though not a smartphone, Jiophone (https://www.jio.com/en-in/jiophone) can be used to access the MPA. Several farmers in the study region had been using Jio phone to access MPA. Because smartphone access is a necessary but not sufficient condition for app usage, our analysis focuses on randomized encouragement and usage rather than device type. All the sample villages had an active cellular network and internet coverage.

was collected after random assignment, the distribution of crops is expected to be balanced across treatment and control groups. Following the orientation, we randomly divided the farmers into two groups: Treatment (n = 510) and control (n = 496). Randomisation was done at the individual-farmer level, so each village had both treatment and control farmers. Because the intervention involved information that could potentially spill over among farmers, this individual-level randomisation within villages was chosen to measure direct effects while acknowledging some contamination could occur. To mitigate cross-group information exchange, we kept treatment assignments confidential and ensured villages were geographically dispersed. We randomly assigned farmers to treatment and control groups using an Excel-generated random number[2]. Randomisation was conducted at the individual level, stratified by village, to ensure similar sample sizes across villages. Farmers were assigned within each village by random number, then allocated to treatment or control based on a pre-specified 50–50 split. Treatment assignments were not disclosed to farmers to reduce the risk of spillovers.

The study lasted six months, covering the Rabi 2020–21 cropping season from September 2020 to February 2021[3]. Only the treatment group farmers received SMS reminder messages on their mobile phones during the study period. These text messages encourage farmers to utilise the *Na Panta* app for various farming activities. The messages were sent three times per week, a frequency commonly used in similar interventions, and were tailored to the cropping calendar and features of the app. These periodic SMS reminders were designed to serve as a non-coercive nudge in the traditional framework of 'libertarian paternalism': farmers are not compelled but are gently and repeatedly invited to engage with MPA.

The intervention augments farmers' information while respecting individual autonomy. For example, a typical message might remind farmers to access the app for the latest market prices before selling their harvest, or suggest using the app's pest identification tool during the crop growth stage. All messages were written in Telugu and kept concise and actionable (see *Annexure 1* for a list of messages sent to farmers). Farmers in the control group did not receive any messages beyond the initial training, though they still had access to the app if they chose to use it on their initiative. Throughout the intervention period, we closely monitored farmers' Usage of the *Na Panta* application. The app's backend enabled us to track usage statistics for each participant, including the number of app opens and the duration of use (see Annexure 2 for the *theory of change*). An end-line survey was conducted in February–March 2021, shortly after the Rabi season harvest, to collect outcome data and other supplementary information *(see Figure 2 for study timeline)*. Due to strong local support and engagement, sample attrition was minimal – only about 1% of farmers dropped out by the end line. Attrition in the treatment group was 0.7 percentage points higher than in the control group; however, this difference is small in magnitude and only marginally significant (p = 0.058). To the extent that attrition differs across groups, a higher dropout rate among treated farmers would bias estimated treatment effects downward, since some potentially responsive individuals would no longer be

[2] The randomisation approach was described in the pre-registration.
[3] There are two major crop seasons in Andhra Pradesh (and most of India), namely Kharif and Rabi. Kharif season starts around first week of July (with the onset of the monsoon rains) and continues till September whereas Rabi starts in October and ends in February.

observed. Therefore, our estimates may slightly understate the true treatment effect. Given the low overall attrition rate and the small absolute difference, differential attrition is unlikely to affect the estimated treatment effects materially.

[Insert Figure 2 here]

3.2 Data and Variables

Our analysis uses data from both the app monitoring system and the surveys. We measure adoption of the Na Panta app as a binary indicator: whether farmers installed the app on their smartphones and registered/logged in at least once. By the end of the trial, we recorded whether each farmer had ever installed and accessed the app. This serves as our primary outcome in evaluating the effect of text messages on adoption. Nearly all farmers in the treatment group who installed the app did so within a few weeks of the intervention's start, whereas control farmers' adoption was generally lower and occurred without prompting.

For those who adopted the app, we measure MPA usage intensity along two dimensions: Total Instances Accessed (TIA) and Total Minutes Used (TMU). TIA is the total number of distinct times the farmer opened or logged in to the app during the study period. Each login or access event counts as one instance. TMU is the cumulative time (in minutes) the farmer spent using the app over the period. These two metrics capture different aspects of engagement. TIA reflects how frequently the farmer checked the app, while TMU reflects the depth/duration of the engagement. Importantly, these may diverge – a farmer could open the app many times for very short periods, or use it fewer times for longer sessions.

Since the Usage measures TIA and TMU are non-negative count variables, we additionally estimate Poisson regression models as a robustness check *(Refer Annexure 8)*. Count outcomes are typically right-skewed, may exhibit heteroskedasticity, and are not well described by a linear conditional expectation function. The Poisson model naturally accounts for these properties by modelling:

$$E(Y_i \mid X_i) = \exp(X_i\beta)$$

where Y_i denotes TIA or TMU. We estimate Poisson models with robust standard errors, using the same set of covariates as in the OLS specifications.

To evaluate economic benefits, we collected data on the output prices farmers received for their main crop and the total expenditure on inputs (pesticides and fertilisers) incurred by farmers for the Rabi season crop. For each farmer, we identified the principal crop they cultivated and sold during Rabi 2020–21, and recorded the price per quintal they received for that crop. We focused on two primary farm-level outcomes, i.e., output prices and expenditure on fertilisers and pesticides, because these dimensions are directly linked to the Na Panta app's core functionalities. During the design phase, we consulted both the local agriculture officer and the Na Panta development team to identify which features were most frequently used by farmers and most relevant during the study period. They highlighted two components: (i) daily market-wise price information for major crops, and (ii) a package of practices guide on fertiliser application and pest management, which could affect chemical input use. Given that our evaluation covers a single cropping season, these two outcomes represent the farm-level metrics most likely to respond within the study timeframe and most plausibly tied to the MPA's value proposition.

Data on output prices and input expenditures were collected by trained enumerators using a structured questionnaire. For output prices, farmers reported the quantity sold, the unit of sale, and the total revenue received for their principal crop during the Rabi 2020–21 season. Enumerators verified responses using sales slips or, when available, farmer records. We then computed the average sale price per unit as total revenue divided by quantity sold. For input expenditure, farmers were asked to report all expenses on pesticides and fertilisers for the same crop and season, with enumerators probing for each input purchased and cross-checking with receipts or leftover containers where possible. Total input expenditure was calculated as the sum of expenditure on pesticides and fertilisers.

As the price data were often skewed, we used the inverse hyperbolic sine (IHS) transformation of the price per unit as our dependent variable for the analysis of price realisation. A higher value indicates a better market outcome for the farmer. We apply the IHS transformation to the price-realisation variable because the data contain a substantial number of zero values (140 observations), which makes the standard logarithmic transformation infeasible in our context without excluding a meaningful portion of the sample. IHS is widely used in empirical work as an alternative to the natural log when variables exhibit many zeros or negative values, while retaining a broadly similar interpretation in terms of sign and relative magnitude (Bellemare & Wichman, 2019; Chen & Roth, 202). Following Norton (2022), we acknowledge that the IHS is not scale-invariant and that retransformed marginal effects should be interpreted cautiously. A well-noted limitation of the inverse hyperbolic sine (IHS) transformation is that it provides a poor approximation to the natural logarithmic transformation for small values of the variable ($x < 10$). In our context, however, the parameters of interest are the signs and relative magnitudes of the coefficients rather than precise elasticities, and results estimated at the level confirm that our substantive conclusions remain unchanged.

The farmer's expenditure on inputs (pesticides and fertilisers) is measured in Indian Rupees (₹) as reported in the end-line survey and cross-verified with input purchase records where possible. We focus on these inputs because *Na Panta* provides specific information on pest management and fertiliser application guidelines. In the analysis, we use expenditure levels (rather than logs) as the outcome, since some farmers spent zero on certain inputs, and we are interested in absolute savings in costs. On average, expenditures on fertilisers and pesticides constitute a significant portion of production costs for these crops (often 40–50% of total variable costs in India (Gulati & Banerjee, 2015)), so a reduction in their Usage could be economically meaningful.

We account for various farmer characteristics and other factors affecting adoption or outcomes. From the baseline and end-line surveys, we include controls for the farmer's age, sex (female = 1), education level (years of formal schooling), and landholding size (acres of cultivable land). We also control whether the farmer has access to irrigation (as opposed to solely rainfed farming) and whether they have any non-farm income sources, since these can influence technology uptake and investment capacity. Additionally, we consider the social group (caste) category (whether the farmer belongs to a historically disadvantaged group (Scheduled

Caste/Scheduled Tribe) or another group) and membership in farmer associations or cooperatives. These social factors can affect information dissemination and bargaining power. We also include village-fixed effects in regressions to absorb location-specific influences, such as market access and infrastructure differences, common to farmers in the same village.

The socio-economic profile of our sample, as captured in the baseline, aligns with that of a typical smallholder farming community in the region (see *Table 1)*. The average farmer was about 45 years old, and only 5–6% were under 30, reflecting the trend of rural youth moving into non-farm jobs. Most respondents (83%) were male, as women often did not self-identify as the primary farmer even if they participated in farm work. Education levels were low: farmers had an average of about 5 years of schooling, and nearly one-third had no formal education. The average landholding was around 5 acres, and about 56% of farmers had some irrigation facilities. At baseline, all farmers were new to smartphone-based agricultural apps; none had used *Na Panta* before, and very few were aware of it. We have verified the balance between the treatment and control groups and found that, due to random assignment, they were broadly similar in demographics and farm characteristics. Differences in means are estimated using regression models for each covariate, with the treatment indicator and standard errors clustered at the village level. Reported p-values correspond to these clustered regressions. We regressed treatment assignment on the full set of baseline covariates and tested the joint significance of the covariates. The resulting test statistic, $F(10, 13) = 1.62$, $p = 0.2037$, indicates that we cannot reject the null hypothesis that treatment assignment is orthogonal to baseline characteristics. We control for all these variables in regression models to ensure they do not bias the treatment effect estimates.

Table 1 – Descriptive statistics of the sample

Variable	**Sample (1006)**		**Control (4096)**		**Treatment (510)**		**Δ T & C**	**P value**[>]
	Mean	**SD/%**	**Mean**	**SD/%**	**Mean**	**SD%**		
Age of farmer	45.55	16.11	48.76	19.00	42.44	11.92	-6.31	0.06
Farmer education (in years)	5.57	5.38	4.93	5.64	6.19	5.04	1.26	0.10
Sex: Male	0.83	0.37	0.78	0.41	0.89	0.32	0.11	0.07
Smartphone	0.42	0.49	0.42	0.49	0.43	0.49	0.01	0.14
Other Income: Yes	0.35	0.48	0.26	0.44	0.44	0.50	0.18	0.18
DMC Score[#]	34.01	14.72	37.85	12.65	30.27	15.62	-7.58	0.19
Irrigated: Yes	0.44	0.50	0.58	0.49	0.31	0.46	-0.27	0.10
Association Membership	0.51	0.50	0.29	0.46	0.72	0.45	0.44	0.02
Owned land	5.02	4.99	4.57	5.51	5.45	4.39	0.88	0.54
Social groups categories*								
OC	0.34	0.47	0.31	0.46	0.38	0.48		0.89
OBC	0.51	0.50	0.52	0.49	0.50	0.50		
SC	0.07	0.27	0.04	0.20	0.11	0.31		
ST	0.06	0.23	0.12	0.32	0.00	0.00		
Owned land categorisation								
Marginal farmers (<2.5 acres)	318	31.6%	205	41.3%	113	22.1%		0.08
Small farmers (2.5 – 5 acres)	320	31.8%	155	31.2%	165	32.3%		
Medium farmers (5 – 25 acres)	363	36.8%	132	26.6%	230	45.1%		

Large farmers (> 25 acres)	5	0.5%	3	0.6%	2	0.4%		

DMC score: Decision-making capabilities score adapted from Ali and Kumar (2011).

* Social group categories consist of - OC – Other castes, OBC – other backward castes, SC – Scheduled castes, ST – Scheduled Tribes

> P-values obtained by regressing each covariate on treatment, clustering standard errors at the village level.

3.3 Empirical Strategy

To estimate the impact of the text message intervention on farmers' adoption and use of the *Na Panta* app, we conduct an intent-to-treat (ITT) analysis. In its simplest form, this can be viewed through mean comparisons between the treatment and control groups. We quantify the number of farmers in each group who installed the app (adoption rate) and the average usage intensity (TIA and TMU) for each group. We then estimate regression models of the form:

$$Adoption_i = \beta_0 + \beta_1 Treatment_i + \beta_2 X_i + u_i \text{ - (1)}$$

$$Usage_i = \beta_0 + \beta_1 Treatment_i + \beta_2 X_i + v_i \text{ - (2)}$$

where $Treatment_i$ is a dummy for whether farmer i was assigned to receive SMS reminders, and X_i is a vector of control variables (as described above) to account for any residual imbalances and improve precision. The coefficient β_1 in equation 1 captures the causal effect of being encouraged on the probability of adopting the app, and β_1 in equation 2 captures the effect on usage intensity. Because treatment was randomised, these coefficients can be interpreted as intention-to-treat estimates. We estimate linear probability models for adoption, which yield results similar to those of logit and OLS for usage outcomes. Standard errors are clustered at the village level to allow for intra-village correlation.

To obtain a causal estimate of the impact of the mobile app's Usage on prices realised and expenditure on pesticides and fertilisers, we employ an instrumental variables (IV) approach, using the randomised SMS intervention as an instrument for app usage. Estimating the causal effect of MPA usage requires acknowledging the fact that Usage is not randomly assigned. Farmers choose whether and how intensively to engage with the MPA, and this decision is likely correlated with unobservable characteristics such as motivation, information-seeking behavior, managerial ability, or prior knowledge. These unobserved factors may also influence input expenditure and price realisation, generating endogeneity concerns if adoption/usage is included directly in an OLS model. We conduct formal endogeneity tests. Using the randomised SMS encouragement as an instrument, the Anderson–Rubin endogeneity test rejects the null of exogeneity, indicating that Usage is endogenous. The first-stage Sanderson–Windmeijer F-statistic exceeds the Stock–Yogo critical values, confirming that the instrument is strong and that weak identification is not a concern. To address this, we use randomised SMS reminders as an instrumental variable, providing exogenous variation in MPA app usage independent of these underlying farmer characteristics.

In essence, the random assignment provides exogenous variation in Usage: the treatment group had a higher propensity to use the app due to the encouragement, independent of their other characteristics. This allows us to isolate the local average treatment effect (LATE) of Usage on outcomes. These estimates reflect the average treatment effect among those members who always comply with their assignment. We estimate each impact variable's two-stage least squares (2SLS) regression model.

$$U_i = \pi + \phi Treatment_{\ i} + \Lambda X_i \ + \ \varepsilon_i \text{ - (3)}$$

$$Y_i = \delta + \theta \widehat{U}_i + \Psi X_i + e_i \text{ - (4)}$$

In the first stage equation U_i is a measure of Usage. We run separate models for U_i as TIA and as TMU. This first stage gauges how strongly the treatment influences Usage. In the second stage equation (4) Y_i is the outcome of interest for the farmer i (either inverse hyperbolic sine of price per unit or input expenditure), and $\widehat{U}_i$ is the predicted Usage from the first stage (refer to annexure 3). The coefficient θ is the IV estimate of the effect of app usage on the outcome variables. Intuitively, θ tells us how outcomes differ between users and non-users, accounting for the fact that Usage was increased by random encouragement. We include the same control variables Ψ as used in equations (1) and (2), and village fixed effects in these regressions to improve efficiency.

For the IV to be valid, two conditions are required: (a) Relevance – the SMS treatment significantly affects app usage (first stage is strong), and (b) Exclusion restriction – the SMS treatment affects the outcomes *only* through its effect on app usage, not through any other channel. Condition (a) can be statistically tested by the first-stage F-statistic. In our case, the treatment proved to be a strong predictor of both TIA and TMU, with F-statistics well above the conventional threshold *(refer to Annexure 3)*, indicating no weak instrument problem. In the first-stage regressions, the coefficient on the SMS treatment is positive and statistically significant for both app usage measures (TIA and TMU), with t-statistics of 8.66 and 4.96, respectively. The corresponding first-stage F-statistics are 38.31 and 12.33, both exceeding the conventional Staiger and Stock (1997) threshold of 10, indicating that the instruments are relevant. Condition (b) is plausible here because the assignment was random and consequently had no influence on the Usage of MPA apart from the encouragement provided through text messages. Thus, any impact of the SMS on prices or input spending would logically operate via the farmer using the app. We also performed tests for over-identification in some variants, using multiple instruments to check whether the instrumented model was consistent; these tests did not indicate any violation of exclusion ($p > 0.1$).

4. Results

4.1 Text messages and MPA Adoption

The results from the RCT experiment show a significant positive impact of the SMS intervention on app adoption (see Table 2). By the end of the study, farmers in the treatment group were about 11 percent more likely to have installed and started using the app than those in the control group. In the treatment group (who received reminders), a substantial proportion of farmers adopted *Na Panta*, whereas adoption in the control group remained low. In practice, many farmers installed the app after receiving several prompts emphasising its benefits for farming decisions. This suggests that lack of awareness or attention could have been a key barrier that the reminders helped overcome.

During the focus group discussions, treatment farmers mentioned that the repeated messages kept them curious and reminded them that "this app might help us," leading them to try it out. Control farmers, in contrast, often forgot about the app after the initial introduction or were not sufficiently motivated without further prompting. For the binary adoption outcome, we estimate both a linear probability model (LPM) and a logit model. The LPM delivers a statistically significant treatment effect, while the logit model yields a marginal effect of similar sign and magnitude but estimated less precisely, and hence not significant at conventional levels. Given that our interest lies in the average treatment effect in a randomised design, we present LPM estimates in the main text and report logit results as a robustness check in *Annexure 7* (Angrist and Pischke, 2009).

Beyond the binary adoption outcome, we examined the intensity of app usage through the two metrics: login instances (TIA) and time spent (TMU) (refer to Table 3). Here, we find a nuanced result: the SMS led to more frequent app access but not necessarily more prolonged use. Treatment farmers logged into the *Na Panta app* significantly more times (nearly 38 more times) on average than control farmers. This difference is statistically significant and meaningful in magnitude – essentially, the reminders succeeded in getting farmers to open the app regularly. Many treatment farmers would check the app briefly whenever they received a reminder. However, regarding total minutes of use, the data show no significant difference between treatment and control groups. The reminders, therefore, did not increase the overall time spent engaging with the app's content. Indeed, regression results show that the treatment effect on TMU was positive in a simple model but became insignificant after controlling for farmer characteristics. Poisson regression results confirm the main findings obtained from OLS. The treatment significantly increases TIA, while effects on TMU remain small and imprecise. The magnitudes and directions of the Poisson coefficients are consistent with the linear estimates, indicating that the functional form assumptions do not drive the key results.

This finding suggests that while text messages can stimulate initial interest and routine checking of the technology, they cannot guarantee deep engagement if the content does not immediately resonate with the user's needs. In our study, farmers in the treatment group often opened the app in response to an SMS, but if they did not find new information relevant to their current concerns, they exited quickly, resulting in usage durations comparable to those in the control group. Although the intervention did not significantly increase total minutes spent on the MPA, focus group discussions helped reconcile this finding with the observed economic benefits. Farmers reported engaging in focused, task-specific Usage rather than prolonged browsing. Many described opening the app briefly to check targeted information (such as pesticide dosage recommendations or prevailing market prices) at specific decision points in the cropping cycle. This pattern suggests that short but purposeful interactions, rather than extended time spent on the platform, were sufficient to influence input-use and marketing decisions.

Table 2: Intention to Treat (ITT) estimates of the intervention on adoption of MPA

Dependent variable: Adoption of MPA (0, 1)		
	ITT estimates	**Adjusted ITT estimates#**
Treatment	0.048*** (0.011)	0.113*** (0.019)
Controls	No	Yes
N	1006	1006
R Squared	0.018	0.1792

*Note: Standard errors adjusted for clustering at the village level in parentheses, *p<0.10, ** p<0.05, *** p<0.01*
Reference group for Sex is Male, Social groups are other castes
 # Adjusted columns control for baseline covariates and village fixed effects

Table 3: Intention to treat (ITT) estimates of TIA and TMU

Dependent variable: MPA Usage				
	TIA	**TIA**	**TMU**	**TMU**
	ITT estimates	**Adjusted ITT estimates#**	**ITT estimates**	**Adjusted ITT estimates**
Treatment	23.99*** (2.62)	37.74** (15.53)	11.58*** (2.83)	25.38 (19.11)
Controls	No	Yes	No	Yes
Average Usage in control group	74.68	-	50.21	-
N	1,006	1,006	1,006	1,006
R Squared	0.0765	0.2129	0.0165	0.094

*Note: Standard errors adjusted for clustering at the village level in parentheses, *p<0.10, ** p<0.05, *** p<0.01*
Reference group for Sex is Male, Social groups is other castes
 # Adjusted columns control for baseline covariates and village fixed effects

4.2 MPA Usage and Farm Outcomes

4.2.1 Impact on Expenditure for Pesticides and Fertilisers

The empirical results on the impact of using the agricultural MPA reveal that the greater use of the *Na Panta* app led to a reduction in farmers' spending on pesticides and fertilisers (Table 4). The IV 2SLS estimates show that both usage measures, TIA and TMU, have a negative and statistically significant (at the 5% level) effect on input expenditure. An increase of one standard deviation in app usage (access frequency or time) was associated with a significant drop in input expenditure. Interestingly, the coefficient on minutes used was even larger in absolute value than on instances accessed, implying that the depth of engagement yields additional benefits. In other words, merely opening the app can help farmers reduce excess input use, but spending more time reading and understanding the information provides greater guidance that can further cut costs. This could imply that a farmer might need to explore the app's recommendations (for example, by reading a detailed article on pest management) to fully implement changes that save money. Our model, in this context, indicates that if a farmer who only occasionally used the app were to use it as frequently as a regular user (say, checking it dozens of times over the season), their spending on fertilisers and pesticides could decrease by roughly ₹100–₹200 (Indian Rupees) per acre ($1.20–$2.40 per acre), all else equal. That represents a notable cost saving given the average cash expenditure on these inputs. While ₹100–200 is about 5–10% of mean chemical input costs in our sample, it can constitute a larger share of net profit margins for smallholders.

In practical terms, these results imply that farmers who engaged more with the app spent less on chemical inputs for the season's crop, holding other factors constant. This effect is consistent with the app's content, which includes guidance on optimal input application and integrated pest management. By using the app, farmers likely obtained information on proper dosages, alternative pest control methods, or timely application schedules, which helped them avoid excessive or unnecessary use of pesticides and fertilisers without altering production practices, thereby improving cost efficiency[4]. Many Indian farmers traditionally rely on input dealers for advice, who may have incentives to oversell products[5]. The app's independent recommendations might have corrected such tendencies, resulting in reduced input. Overall, the MPA usage had multiple benefits: improved input-use efficiency, lower input costs, and potential environmental benefits.

The interpretation of reduced input expenditure may arise through multiple channels. One possibility is that farmers purchased the same quantities at lower prices—for example, by avoiding unnecessary products or better timing their purchases—thereby improving cost efficiency without altering production practices. Another possibility is that farmers reduced the actual quantity of fertilisers or pesticides applied. This mechanism is plausible in our context, as insights from the pilot phase revealed that many farmers relied heavily on dealer advice and tended to over-apply fertilisers as a precautionary strategy. The app's dosage recommendations and pest-management guidance may therefore have helped correct such overuse. These channels have different implications: the former reflects improved purchasing efficiency, while the latter may yield both economic gains and potential environmental benefits. While the short evaluation period limits our ability to disentangle these mechanisms fully, the observed decline in expenditure is best interpreted as evidence of improved input-use efficiency rather than simple cost-cutting.

[4] The *Na Panta* app provides dosage recommendations and pest-management guidance to farmers.

[5] Insights from our pilot phase revealed that many farmers relied heavily on dealer advice and tended to over-apply fertilizers as a precautionary strategy

Table 4: IV 2SLS estimates of MPA usage on expenditure on pesticides and fertilisers

Dependent variable: Expenditure on Pesticides and fertilisers				
	IV 2SLS Estimates	**IV 2SLS Estimates**	**IV 2SLS Estimates**	**IV 2SLS Estimates**
Total Instances Accessed (TIA)	-115.71** (49.10)	-106.2* (50.24)		
Total Minutes Used (TMU)			-226.99* (113.66)	-187.03* (88.95)
Controls	No	Yes	No	Yes
Average expenditure	26,612	-	26,612	-
N	997	921	997	921
Wald F statistic	40.93	38.31	8.33	12.33
LM statistic (Chi-square)	75.86 (0.00)	72.78 (0.00)	16.53 (0.00)	24.75 (0.00)
Sargan statistic (Chi-square)	10.98 (0.00)	2.42 (0.12)	9.08 (0.002)	1.47 (0.22)
F test (Prob > F)	5.44 (0.018)	1.65 (0.022)	3.98 (0.046)	1.43 (0.075)

Note: Instrument: Treatment. Standard errors adjusted for clustering at the village level in parentheses. * p<0.05, ** p<0.01, *** p<0.001

These results align with findings from other contexts that better-informed farmers can achieve more with less. Small and marginal farmers in developing countries often overuse fertilisers or pesticides due to misinformation or precautionary habits. By correcting these practices, information apps can contribute to economic and environmental gains. Some related factors from our regression controls are worth noting: farmers with larger landholdings had significantly lower per-acre input expenditures, and those with irrigation access also spent less on inputs compared to small rainfed farmers. This matches broader patterns – larger farmers often achieve economies of scale in input purchasing and use (Ramaseshan, 2022), and irrigation enables more efficient input application (e.g., fertigation, controlled timing). The fact that our treatment effect persists even after accounting for land size and irrigation suggests the app had an independent cost-reducing influence applicable to all farmers. It is also a positive sign for resource conservation: reduced chemical inputs save farmers money and imply less chemical runoff and environmental harm, a co-benefit we return to in conclusion.

4.2.2 Impact on Crop Price Realisation

The IV estimates for the price received per unit show a positive, statistically significant effect of app usage (Table 5), suggesting that farmers who used the Na Panta app more intensively received better prices for their harvest. The point estimates suggest that a farmer with high app usage (one standard deviation above the mean) attained prices several percentage points higher than a comparable farmer who rarely used the app. Both the frequency of access and the time spent on the app contributed to this improvement, with time spent (TMU) again showing a somewhat larger effect. This indicates that farmers who regularly used the app could get better prices.

Table 5: IV 2SLS estimates of MPA usage on farmers' price realisation per unit

Dependent variable: Farmers' price realisation per unit				
	IV 2SLS Estimates	**IV 2SLS Estimates**	**IV 2SLS Estimates**	**IV 2SLS Estimates**
Total Instances Accessed (TIA)	0.024** (0.002)	0.016* (0.008)		
Total Minutes Used (TMU)			0.049* (0.019)	0.027* (0.013)
Controls	No	Yes	No	Yes
Average price realised	2,279	-	2,279	-
N	921	921	921	921
Wald F statistic	40.931	38.314	8.382	12.33
LM statistic (Chi-square)	75.861 (0.00)	72.785 (0.00)	16.536 (0.003)	24.756 (0.00)
Sargan statistic (Chi-square)	2.497 (0.114)	0.157 (0.691)	1.944 (0.163)	0.023 (0.878)
F test (Prob > F)	9.35 (0.0023)	2.55 (0.00)	6.22 (0.012)	2.26 (0.00)

Note: Instrument: Treatment. Standard errors adjusted for clustering at the village level in parentheses. * p<0.05, ** p<0.01, *** p<0.001

How exactly might using the app lead to higher prices? One mechanism is through better market information and arbitrage opportunities. *Na Panta* provided daily price listings from nearby markets and mandi (wholesale market) yards. Qualitative discussions indicate that farmers using the app were able to monitor these prices and choose when and where to sell their produce more strategically. For instance, a farmer might delay selling if the app indicates that prices typically rise a few weeks after harvest or might transport produce to a larger market town (outside the farm gate)[6] if prices there are higher than those offered by the local village trader. By exploiting spatial and temporal arbitrage, informed farmers can secure better terms of trade (Barrett et al., 2020). Access to daily farmers' market prices has also strengthened farmers' bargaining position with village traders. While a few farmers had the means to transport produce to distant markets, others had to depend on the traders for transportation, a widely prevalent practice in India.

The farmers from marginalised Scheduled Caste (SC) groups realised higher crop prices than others when they used the app. This finding suggests that marginalised sections of farmers could overcome their constraints, such as discrimination in market access and low bargaining power, by using the Na Panta app and realising higher prices. This could be because such

[6] Prior studies have shown that selling directly in larger markets or outside the village can increase the price received (Minten & Kyle, 1999; Negi et al., 2018)

farmers typically had weaker access to reliable market information before the intervention; even modest improvements in transparency significantly improved their ability to negotiate fair prices.

The gender of the farmer influenced farmers' price realisation. In the regression with TIA as the usage measure, the coefficient on females was significantly negative, implying that women farmers received lower prices than their male counterparts, even when using the app. This gender price gap aligns with broader findings that women farmers often have less access to markets and face systemic biases (Ball, 2020; Spieldoch, 2007), such as reduced mobility, lower participation in market transactions, and a greater reliance on male household members for selling output, all of which limit their ability to leverage market information. These structural barriers might have prevented improved information from translating into comparable price gains for women, despite receiving the same intervention. During our focus group discussions, women in the study villages reported that they rarely visited distant markets themselves; they either sold at the farm gate or had male relatives sell on their behalf, which can lead to lower negotiated prices. While the app provides the same information to everyone, the ability to act on that information (e.g. travel to a market or haggle with buyers) may still be constrained for women. Thus, the app alone did not eliminate the gender price gap.

These findings highlight that complementary policy interventions, such as improving women's access to transport or collective marketing, may be needed to ensure that App usage has a beneficial impact on reducing input costs and increasing output prices. These improvements can directly raise farmers' net income by enabling them to earn higher revenue and reduce input costs. Overall, our findings make a strong case that digital information interventions can lead to tangible economic benefits for farmers, but realising these benefits at scale will require both promoting adoption and ensuring continued Usage.

4.3 Alternative Specifications

We analysed three alternate specifications using complementary estimation strategies to validate the main findings. First, sequential ordinary least squares (OLS) regression models were used to estimate the intent-to-treat (ITT) effects on three dependent variables: adoption of mobile phone applications (MPA), total instances accessed (TIA), and total minutes used (TMU). Two model specifications were estimated for each outcome: a baseline model with only the treatment indicator and a fully adjusted model including demographic, socio-economic, and network-related controls. Second, quantile regression was conducted on total instances accessed (TIA) to examine whether the treatment effect varied across the distribution of access frequencies. This method provides insights beyond average effects, showing how different types of users, ranging from low to high engagement, responded to the intervention. Third, similar quantile regression models were estimated for total minutes used (TMU), capturing variation in the depth of engagement with the technology platform across user groups.

The results from the alternate specifications reaffirm the positive impact of the agricultural technology intervention on key outcome variables. The intervention significantly increased the adoption of mobile phone applications, total instances of platform access, and total minutes of

Usage, with consistent and statistically significant treatment effects observed for adoption and access metrics across multiple model specifications (Annexure 4). These effects remained robust even after controlling for farmer characteristics such as age, education, landholding, and decision-making capacity. Importantly, the decision-making capacity (DMC score) and land ownership were positively associated with better outcomes, indicating that farmers with greater agency and resources were more likely to benefit from the intervention.

Further validation using quantile regression models demonstrates that the intervention had meaningful impacts at the mean and across the distribution of users. The treatment effect on total instances accessed was particularly strong in the lower and median quantiles, suggesting that the intervention helped engage even the less active users (Annexure 5). While the effect on total minutes used was positive across quantiles, statistical significance was weaker, indicating greater variability in the depth of use among farmers (Annexure 6). Overall, these robustness checks strongly support the study's main findings on the intervention's role in enhancing technology adoption and digital engagement in agriculture.

As randomisation was conducted at the individual rather than village level, farmers within the same village were assigned to different treatment conditions. This design raises the possibility of spillovers, i.e., treated farmers discussing the app or the reminder messages with control farmers. As we did not collect direct measures of farmer-to-farmer communication, we acknowledge the possibility of within-village spillovers. Any such spillover tends to reduce the observable differences between the treatment and control groups, thereby biasing the intention-to-treat (ITT) estimates toward zero rather than inflating them. In this sense, the effects reported in this paper should be interpreted as conservative, lower-bound estimates of the intervention's true causal impact. As a robustness check against potential within-village spillovers, we computed a treatment saturation measure for each village (the proportion of sampled farmers assigned to the treatment group). Among control farmers only, we regressed key outcomes on this saturation variable with village-clustered standard errors. Annexure 9 shows that the coefficients are small in magnitude and statistically insignificant. These results provide no evidence that control farmers' outcomes systematically vary with village-level treatment exposure, suggesting that any spillover effects are unlikely to be large.

5. Summary and Policy Implications

This study examined the impact of sending text messages on encouraging Indian farmers to adopt and use a smartphone-based agricultural information application, and the impact of application use on prices realised and farmers' expenditure on pesticides and fertilisers. The results reveal that text message reminders can significantly influence farmers' adoption of the MPA (*Na Panta*), which is the focus of this study. This result is encouraging for policymakers and development practitioners, as it demonstrates that sending bulk text messages is a cost-effective method to increase the adoption of digital agriculture technology. Therefore, incorporating text reminders into the government's agricultural technology adoption strategies would improve adoption rates.

However, our results also highlight that initial technology adoption does not automatically translate into intensive use. The text messages prompted farmers to log in to the mobile app but did not substantially increase the time they spent absorbing the information. For development programs aiming to leverage digital tools, this implies that the quality of use matters. Introducing an app to farmers is the first hurdle; the next challenge is to ensure the content is engaging, credible, and relevant enough that farmers keep using it without constant prompting. Therefore, efforts must be made to improve the relevance and user experience of agricultural apps. For instance, customising information to the local context, updating content frequently, and adding interactive features could make farmers more eager to spend time on the app. In our case, many farmers reported using *Na Panta* more when it offered even more localised weather forecasts or could diagnose crop diseases from photos. Such feedback can guide app developers and sponsors in the next iteration of digital extension tools. Furthermore, while our study employed a reminder frequency (three SMS per week) consistent with prior work, we acknowledge that higher intensities could lead to message fatigue or reduced attention from farmers. Future research that experimentally varies reminder frequency would help identify optimal dosage levels and potential non-linearities in responsiveness.

Our findings established that farmers who used the Na Panta app benefited in measurable ways; they reduced their input costs for pesticides and fertilisers and obtained higher prices for their crops. These improvements carry significant implications for farmer outcomes. Lower input expenditure means improved cost efficiency and potentially higher profit margins for farmers. In aggregate, if many farmers reduce unnecessary pesticides and fertilisers, there are environmental benefits such as less chemical runoff, improved soil health, slower development of pest resistance, fiscal benefits from reduced fertiliser subsidies, and health benefits for farmers and consumers. The observed reduction in input expenditures is plausibly explained by Na Panta's role in improving input-use efficiency. Before the intervention, farmers often relied on peer recommendations or input dealers, which may have led to excessive or sub-optimal application of fertilisers and pesticides. Studies have shown that smallholders in India frequently overapply agrochemicals due to a lack of tailored, timely information (Fan & Gan, 2025; Ding et al., 2022). Na Panta provided localised, crop-specific advisories that may have enabled farmers to match input use to actual crop needs better, thereby reducing unnecessary expenditures without compromising yields. Moreover, improved information on pest management and soil health could have helped farmers adopt more preventive, cost-effective strategies, thereby reducing reliance on chemical inputs.

The ability to time sales or choose advantageous markets can help farmers capture a larger share of the value chain. This is particularly pertinent where farmers often lack bargaining power. Digital platforms that disseminate market price information (like *Na Panta* did) effectively arm farmers with knowledge that can offset traditional information asymmetries between small producers and traders. Over time, if such practices become widespread, they could lead to more efficient and equitable markets, benefiting farmers collectively. The finding that even farmers from historically disadvantaged SC groups could secure competitive prices when using the app is an optimistic sign that technology can serve as a social leveller. The finding that female farmers using the mobile app realised lower prices suggests that technology alone might not close the gender gap – complementary measures to support women farmers in market engagement are needed so that the digital agricultural revolution becomes gender-inclusive. While assessing agricultural profits or return on investment (ROI) would strengthen the analysis, the study's short duration limits the ability to capture longer-term economic impacts. This is acknowledged as a limitation and presents an opportunity for future research using a longer evaluation horizon and more comprehensive economic data.

In conclusion, our combined findings illustrate a pathway for leveraging digital technology to support small farmers: use low-cost text reminders to drive adoption and ensure the technology delivers actionable information that leads to cost savings and better revenues. When these pieces come together, even resource-constrained farmers can improve their profitability and resilience. As smartphone penetration continues to rise rapidly in rural areas, scaling up mobile agricultural services could become a cornerstone of modern extension systems. Governments and development organisations should consider partnerships with Agri-tech start-ups to integrate MPAs into agriculture extension programs. Moreover, investing in rural digital infrastructure and digital literacy will be important to expand the reach of such interventions. Engaging the youth in agriculture could be another strategic move. Younger farmers are generally more tech-savvy and can champion the use of apps, demonstrating their value to older farmers who currently make up the bulk of the farming population in India.

While this study focused on information and encouragement, it opens questions for further research: How can we maintain long-term Usage of agricultural apps without continuous external encouragement? What are the best practices for designing content that maximises impact on farm decisions? Can social features, such as chat groups within apps, enhance knowledge sharing and outcomes? And importantly, what are the effects on broader welfare indicators? Does increased income from better prices and reduced costs lead to tangible improvements in farmers' living standards over time? Addressing these questions will be vital as we seek to harness digital innovations for sustainable and inclusive agricultural development.

Declaration of interests: None

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