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Does telecommunications reinforce rural agricultural extension services: Insights from tribal villages in Eastern India

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ADB Working Paper Series

DOES TELECOMMUNICATIONS REINFORCE RURAL AGRICULTURAL EXTENSION SERVICES: INSIGHTS FROM TRIBAL VILLAGES IN EASTERN INDIA

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In 2011, the Government of India approved the name change of the State of Orissa to Odisha. This document reflects this change.

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Abstract

Conventional agricultural extension services in rural India have been insufficient due to various constraints, including accessibility, finances, and lack of access to other resources. These services primarily depend on in-person visits and physical demonstrations of farming practices, making them only feasible for some farmers. The increasing use of digital and telecommunications technology in rural areas has created an opportunity to improve extension services. This study examines how telecommunications support extension services impact crop productivity among farmers in tribal communities in Odisha, India. The study used a data envelopment analysis (DEA) model to measure the productive efficiency of 513 paddy cultivators in Odisha. Additionally, an endogenous switching regression model was employed to assess the impact of telecommunication-based extension services on technical efficiency scores while controlling for other variables. The study also considered the probability of telecommunication-based extension services influencing the adoption of climate-smart agricultural practices (CSA). The results show that over 80% of paddy cultivators in the region exhibited low farming efficiency. The overall technical efficiency of these cultivators ranged from 0.02 to 1, with an average efficiency score of 0.14. The empirical findings revealed mixed effects of telecommunication-based extension services on paddy cultivation. The telecommunication-based extension services did not unequivocally improve farm productivity, but did positively influence farmers' adoption of Climate-Smart Agriculture (CSA) practices. Given the low levels of education and technical understanding among farmers in the study area, telecommunication-based extension has yet to lead to greater farm efficiency. However, telecommunication-based extension has significant potential to complement physical extension services. Although farmers currently prefer physical extension due to its two-way communication and familiarity, the government can make telecommunication-based extension more user-friendly through better planning and design. There is a need for policy action to develop targeted digital infrastructure to meet farmers' needs effectively.

Keywords: digital extension, data envelopment analysis, endogenous switching regression, climate-smart agriculture

JEL Classification: Q12, Q55, O33, L86

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1. INTRODUCTION

The agriculture and allied sectors accounted for about an 18.3% share of gross value added in the Indian economy in 2022–23 and employed 46% of the total workforce population (Sharma 2023). The agricultural sector in developing countries is dominated by small and marginal farmers (less than 2 hectares of land). Consequently, this led to slow adoption of technology and hindered growth in the sector. Lower agriculture productivity coupled with climate stress would burden the overall production, causing inflationary pressure on food prices. These challenges in agriculture are expected to increase poverty levels in many countries by threatening food security. Governments around the world have formulated various strategies to revive the agriculture sector through greater access to credit, product market linkages, agricultural extension services, subsidies, and awareness programs. Past studies have noted that access to extension services is an essential support for farmers in relation to overall agriculture development (Mazhar et al. 2021; Tanti et al. 2022). Increased climate extremes require a region-specific adaptation for sustainable development. Extension services can impart technical knowledge and create the ability to adopt these technologies to reduce the risks and uncertainties faced by farmers. The primary role of extension is to improve farmer decision-making and the skills needed to enhance agricultural productivity. In addition, agricultural extension services are not limited only to the transfer of technology and improvement in productivity but also address rural challenges such as poverty and food insecurity.

The effectiveness of traditional agriculture extension services is limited in nature due to challenges in the funding, a lack of outreach to individual farmers, and a gap in providing on-site support to the farmers (Taylor and Bhasme 2018; Takahashi, Muraoka, and Otsuka 2020; Tanti et al. 2022). The recent development in mobile phone penetration across the world, especially in developing countries, has improved the access to information, digital services and telecommunications. Telecommunication-based extension services (TES) help in reducing cost in the communication and transfer of knowledge. Mobile phones are the tools used for communicating and disseminating information among farmers. Following this assumption, several studies have focused on evaluating the role played by such services for extension in agriculture development. These studies examined the impact of extension activities on productivity, efficiency, output income, and other variables of interest (Aker and Mbiti 2010; Aker 2011; Ghosh 2012; Benjamin 2013; Rajkhowa and Qaim 2021). However, studies focusing on the evaluation of TES in relation to farm efficiency and technology adoption are limited. In addition, the dynamics of extension services in disadvantageous regions have not been widely studied. Against this backdrop, the present study has two objectives: First, it estimates the impact of TES on crop input-output usage efficiency; and second, it examines the impact of such services in relation to adoption of climate-smart agricultural (CSA) practices.

The remainder of the paper continues as follows: Section 2 presents a brief literature review; Section 3 provides an overview of the study area, data, variables, and methods adopted in the analysis; Section 4 presents the results and discussion while the final section concludes the study.

2. LITERATURE REVIEW

Agriculture extension services are the major drivers for transferring technology, supporting the learning process for rural farmers, assisting them in the decision-making process, transforming the technological advancement to all rural stakeholders, and improving overall rural well-being. Here, we present a brief discussion of studies demonstrating the crucial role of agricultural extension in supporting rural farmers. In Zambia, frequent on-site demonstrations and awareness campaigns about modern technologies by extension workers have improved the rates of adoption of an improved variety of maize (Khonje et al. 2015). Access to extension services has had a significant positive influence on the adoption of agroforestry in the Wayu district of Ethiopia (Kifle, Ayalew, and Mulugeta 2022). Owens, Hoddinott, and Kinsey (2003) reported a 15% gain in crop productivity due to extension access in rural Zimbabwe. Further, Qiao et al. (2022) suggested that agricultural extension services have a significant positive effect on farmers' willingness to use organic fertilizer, where intensification of the application of organic fertilizers can be channelized through agriculture extension services.

Extension services are instrumental in adopting climate-smart technologies that help farmers to adapt to adverse effects of climate change. Climate change threats are impeding farming and therefore suitable adaptation measures need to be made available to farmers to improve farm efficiency. Climate change adaptation is highly region-specific based on climatic, environmental, socioeconomic, and political conditions. Households require technical knowledge to adopt new technological innovations. Thus, such transformation of technical knowledge is addressed by extension services. Past studies found that a lack of knowledge and low realization of the benefits of CSA practices act as major constraints in CSA adoption (Marenja, Gebremariam, and Jaleta 2020). In addition, studies by Aryal et al. (2018) and Yitayew et al. (2021) established that extension services crucially led to greater adoption of CSA practices. Factors such as government extension services and farmer field school participation are the major determinants of CSA adoption (Tanti et al. 2022). Further, Tanti and Jena (2023) found that a lack of ground-level effectiveness in executing extension services makes it difficult for farmers to adopt CSA practices. Thus, designing region-specific extension services is crucial in augmenting the adoption of CSA practices.

There is substantial evidence that extension services are a primary source of information for farmers. However, several significant challenges remain, including the inadequate design of extension services and the barriers to reaching the extensive rural population. Often, the adoption of these services by farmers is limited to the efforts made by extension services, as they may not be tailored to the specific conditions and needs of the farmers (Siddiqui and Mirani 2012). It is observed that extension services are poorly designed with untrained extension workers and lack the necessary infrastructure required along with adequate personnel (Ghosh 2012; Benjamin 2013). Similarly, studies indicate that poor access to information from extension services limits the adoption of improved crop varieties among farmers (Shiferaw et al. 2015).

Given that agricultural extension services are a crucial element of farmers' support system in developing countries and the physical mode of extension support is not fully operational, the digital mode of extension services is gaining importance among the scientific community and policymakers. A significant penetration of smart mobile phones and Internet access in rural areas has made them a viable option for reaching out to a larger proportion of the rural population. Digital extension, if properly designed,

may reduce communication and transaction costs, increase market efficiency, promote economic development, and reduce poverty. Studies have established that digital extension enables a wide range of information dissemination, increases geographic coverage, and offers two-way communication (Aker and Mbiti 2010; Aker 2011; Rajkhowa and Qaim 2021). Therefore, there is growing interest in the literature in evaluating the effect of TES on agriculture development. The strand of the literature focuses on the effects of information access on rural farmers' performance and market efficiency through the usage of mobile phones and Internet services (Aker and Mbiti 2010; Burga and Barreto 2014). TES focus not only on pricing efficiency but also production efficiency by increasing farmers' knowledge at various stages of crop production; this in turn enhances productivity and income and supports economic development. Other studies in the literature focus primarily on whether digital extension helps in increasing farm productivity and income among rural households (Aker 2011; Baumuller 2018; Rajkhowa and Qaim 2021). Rajkhowa and Qaim (2021) found that adopting personalized TES is positively associated with improved agriculture performance (input intensity, productivity, and income). Contrastingly, Aker and Ksoll (2016) found that mobile phone coverage did not increase crop sales or farmgate prices in Niger. In addition, Mitra et al. (2018) found that improving farmers' access to price information is unlikely to have positive outcomes for farmgate prices.

The diversity of results from the literature indicates that the evidence on the impact of digital services on overall agriculture development is not conclusive yet. Hence, there is a need to probe deeper into the real impact of the usage of digital or telecommunication services on the improvement of agriculture development.

3. MATERIAL AND METHODS

The present study has two major objectives. First, it employs data envelopment analysis (DEA) to measure the farm efficiency of farmers in the tribal region of Odisha. These efficiency scores are analyzed to assess the overall level of agricultural development in the study region. Thereafter, the effect of telecommunication-based extension services (TES) on farm efficiency scores is examined through an endogenous switching regression model. Second, the study investigates the likelihood of telecommunication-based extension services being a significant predictor of farmers' adoption of Climate-Smart Agriculture (CSA) practices.

3.1 Conceptual Framework of the Linkage between Telecommunication-Based Extension Services (TES) and Technology Adoption

Telecommunication-based extension services (TES) include call-based and SMS-based services adopted by farmers to seek information on improving agriculture productivity and technology adoption. Digital access to farmers has increasingly been used to overcome the information inefficiency that previously existed in the absence of mobile phones. The widespread use of mobile phones, along with advancements in agricultural measurement and computational technologies, offers new opportunities to overcome the barriers to providing relevant information. Information and communication technologies (ICTs), particularly mobile phones, enable low-cost, timely, and customized information delivery at scale. Mobile phone communication allows farmers to ask specific questions and request valuable information tailored to their needs. Notably, various video-based interventions for farmers have positively impacted their knowledge and self-reported practices. These initiatives influence the

scale, density, target farmer population, scope of feasible customization, and cost-of-service delivery per farmer. In addition, farmers can also scale the technologies to add value to the innovation and further spread these technologies across other neighboring farmers. Further, the content of messages can be refined and tested with target farmers through in-person or telephonic focus group discussions, interviews, and observations before undergoing rigorous testing.

The present study has used the concept of “telecommunication based extension” on the prevalent pattern of digital or telecommunication with farmers from government sources. The state government of Odisha has implemented various agricultural subsidy schemes. The mobile phone numbers of the beneficiaries of these schemes are listed in the government database. The government agricultural department sends SMSs to these beneficiaries containing information about crop selection, planting dates, fertilizer dosage, and application procedures during the cultivation period. During the harvesting period, the prices of different crops are communicated to the farmers. Further, one-way call-based communication also takes place in which the farmers receive calls, and upon accepting the calls they receive information about inputs and outputs. Apart from this, in the farmers’ field school and training sessions, digital modes of communication such as audio-video clips and PowerPoint presentations are used. Agriculture-based nongovernment organizations (NGOs) make WhatsApp groups of those farmers who have smart mobile phones in their area of jurisdiction to send information about crops and inputs. These are the various modes through which digital extension takes place in the study area of the present study. The respondents were asked whether they participated in any such digital extension activities and, if they did, the frequency of such participation in a year.

Figure 1: Conceptual Framework of Effect of Digital or Telecommunication-based Extension (TES) on Crop Productivity

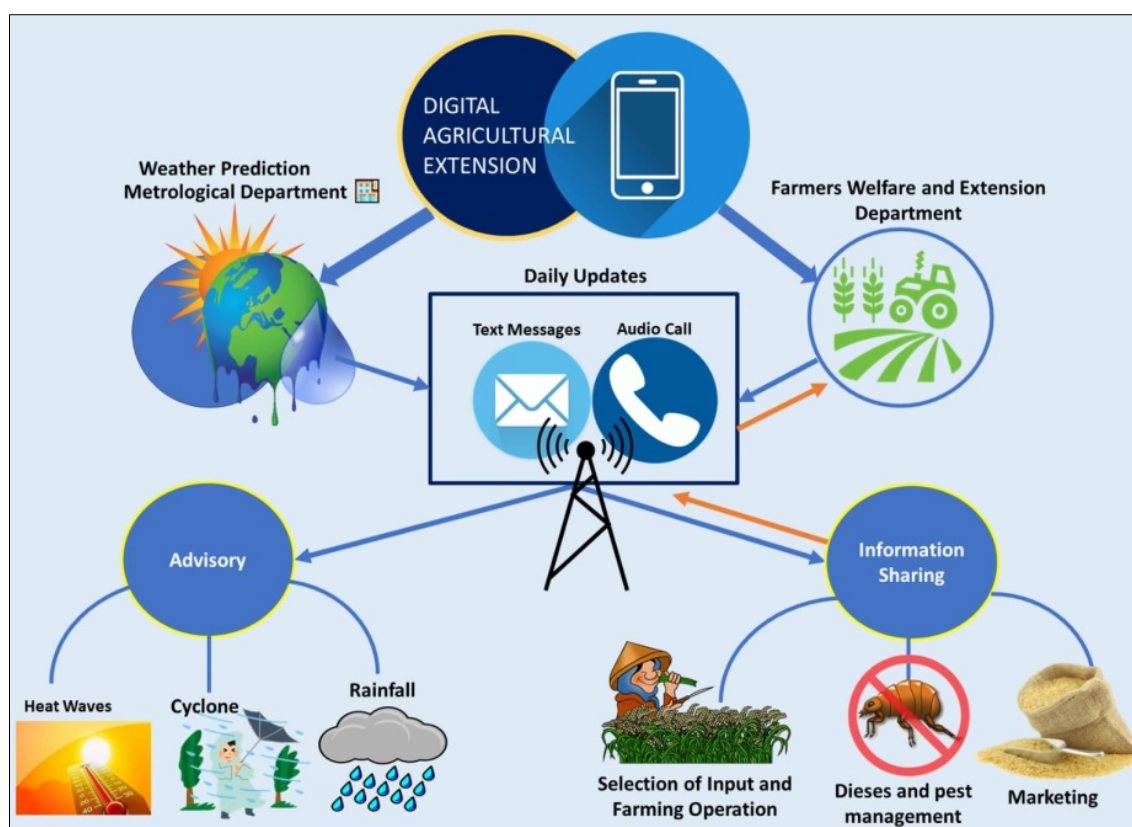


Figure 1 shows the channels through which digital extension affects crop productivity and technology adoption. In India, both the farmers' welfare and extension department and the meteorological department send text- and audio-based weather updates and crop inputs and output information to farmers who are enrolled in these agencies' databases. The central and state governments execute several agricultural policies. The mobile phone numbers of the beneficiary farmers of these schemes are recorded in the government database. These numbers are in turn used by the farmers' welfare and extension department to send text and audio messages to provide information on the precise application of seeds, fertilizers, and pesticides during various stages of farming. At the outset of harvesting, information about the market prices of the crops is made available through these digital modes of communication. In addition, the meteorological department sends messages about weather forecast updates to help the farmers make informed decisions about crop planting dates and the types of crops to be cultivated. This information is part of the digital extension provided to the farmers, which is shown in the upper part of Figure 1. The farmers then use this information to practice precision agriculture and the adoption of sustainable agricultural practices.

3.2 Estimation Techniques

In the first part of the analysis, a data envelopment analysis (DEA) model is used to estimate the efficiency level at which a farmer is operating. The DEA measures the efficiency of the production unit using decision-making units (DMUs). The efficiency is measured with a proportional change in input and output from the sample of DMUs (Lee 2009). The production possibility set first estimates the efficient frontier (equal to one) and decision-making units below the frontier are inefficient. The application of the DEA model can be significantly used in measuring efficiency across various sectors such as from manufacturing to the service industry (Kumar and Gulati 2008). Charnes, Cooper, and Rhodes 1978) measured the efficiency using constant returns to scale, and Banker (1984) used the variable returns to scale efficiency measurement model.

Technical efficiency estimated under constant returns to scale determines efficiency owing to the combination of inputs and output. Technical efficiency has two parts: pure technical efficiency and scale efficiency. Pure technical efficiency indicates farmers' managerial decisions to organize the inputs whereas scale efficiency measures the efficiency at the current level of scale of operation of a farmer. In the present study, the efficiency of paddy cultivators is measured, where paddy yield per hectare (ha) is used as the output and farm labor per ha, fertilizer per ha, and compost used per ha are used as the inputs. A detailed account of the DEA method is presented in Appendix 1.1.

In the second part of the analysis where the impact of the adoption of digital extension is measured on the technical efficiency scores of the farmers, an endogenous switching regression (ESR) model is used. This overcomes the bias of the unobserved variables and explicitly accounts for selection bias and endogeneity simultaneously (Jena 2019). A detailed account of the ESR method is presented in Appendix 1.2.

Finally, in the third part of the analysis, the effect of adopting TES in relation to technology adoption is estimated using a random utility framework (Fischer and Qaim 2014). This model is based on the premise that a household chooses to use a technology if the utility gained from its adoption is higher than a threshold level of utility. A common approach adopted to measure such decisions is known as a "binary choice model" such as a probit or a logit specification. Following this approach, a logit model is estimated in the current analysis. The adoption of a CSA technique is a binary choice in which a farmer chooses to adopt the technique or not to adopt it.

The logit model is explained as follows:

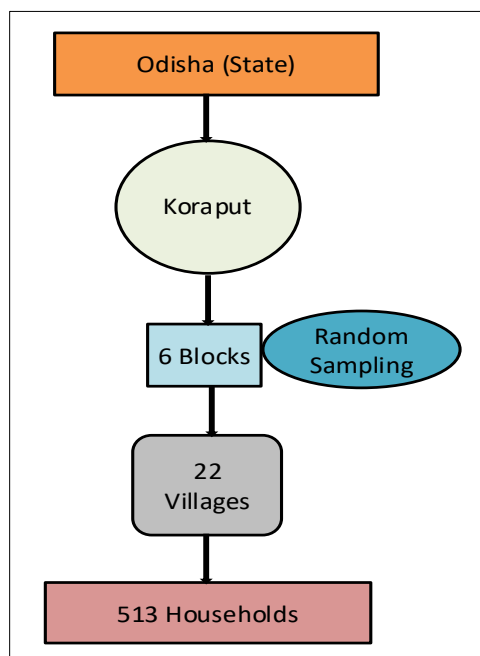
$$\varphi^{-1}(p_i) = \sum_{k=0}^{k=n} \beta_k x_{ik},$$

where $p_i = 1$ if the household adopts CSA practices, and 0 otherwise, and x_{ik} represents the predictors that are used to estimate the probability of adoption (Tanti and Jena 2023). In the predictors' basket, the main variable of interest is digital extension services. Along with these, household sociodemographic, economic, and institutional variables are used as the predictors.

3.3 Sampling, Data, and Variables

Odisha is one of the eastern states of India, where farming is the major occupation and the majority of the population live below the poverty line. The present study focused on the district of Koraput, which has one of the highest concentrations of tribal settlements in the state. Agriculture is the primary occupation in Koraput, with over 90% of the population being engaged in farming or related activities. A multistage sampling approach was employed to conduct a household survey – 22 villages were randomly chosen within the district. Finally, 513 farm households were randomly selected from these villages, with the number of households chosen being proportionate to the size of each village. The sampling design of the study is presented in Figure 2.

Figure 2: The Sampling Design Developed for the Study



The adoption of farm practices by farmers is done through imitating neighboring farmers. This causal mechanism of farmer behavior and adoption varies from region to region. The average paddy yield from the study sample is 2.89 tonnes/ha, while the average derived yield of paddy in Odisha is 4.4 tonnes/ha (DES 2022). The inputs used, such as fertilizer (NPK), comprised around 201 kg/ha for the sampled farmers; however, the average fertilizer consumption in the state is 131 kg/ha (DES 2022). The other major input, i.e., the organic compost used, comprised around 698 kg/ha for sampled farmers, while the state average manure consumption was 1300 kg/ha

(DES 2022). Finally, the average labor person-days used was 81 days per ha for the sampled farmers in the study region. The average size of farm holding among the sampled farmers was about 0.72 ha. Approximately 43 years was the average age of the household head, with an average of 3.80 years of schooling. The average family size among the respondents in the region was five members. Nearly 10 km was the nearest distance to the input market (seed and fertilizer) in the region. Around 22 years was the average farming experience of the household head. In the study sample, 37% of the paddy cultivators stated that they consumed alcohol and cigarettes, while 63% of them didn't consume either. Subsequently, 27% of the paddy cultivators acknowledged that they had other secondary sources of income apart from agriculture income, and 73% of them didn't have any other secondary source of income.

Table 1: Summary Statistics

Variables	Variable Description	Mean	SD
Yield (tonnes per ha)	Total paddy production (tonnes per ha)	2.89	1.52
Farm size (ha)	Farm size (ha)	0.72	0.62
Labor in man-days	Total labor committed to the plot in male/female person days	81	51
Fertilizer (NPK) in kg per ha	Total NPK fertilizer (kg per ha)	201	151
Compost in kg per ha	Total compost used in cultivation (kg per ha)	698	981
Age of the HH in years	Household head age (years)	43	11
Education of the HH in years	Household head number of years of schooling (years)	3.8	3.9
Farming experience of HH in years	Household head number of years of experience in farming (years)	22	10
Family size in numbers	Total number of individuals in the family	5	1.6
Distance to seed/fertilizer market (km)	Distance to seed/fertilizer market in kilometers (km)	10.76	6.61
Smoking and drinking	The variables describe whether farmers consume alcohol and cigarettes or not: dummy = 1 if they consume, 0 otherwise; 37% of the paddy cultivators acknowledged consuming alcohol and cigarettes, and 63% of them did not consume either.		
Secondary income diversification	The variables describe whether farmers have diversified into other source of income: dummy = 1 if they have diversified income, 0 otherwise; 27% of the paddy cultivators acknowledged that they had other secondary sources of income apart from agriculture income, and 73% of them didn't have any other secondary source of income.		
Access to digital extension	The variables describe whether farmers have access to digital extension or not: dummy = 1 if they had access, 0 otherwise; 56% of the paddy cultivators acknowledged that they had access to digital extension services, and 44% of them didn't have access.		
Farmyard manure (FYM)	The variables describe whether farmers adopted farmyard manure practices or not: dummy = 1 if they did, 0 otherwise; 87% of the paddy cultivators acknowledged that they adopted FYM practices, and 13% of them did not.		
Change in planting date	The variables describe whether farmers changed planting dates or not: dummy = 1 if they did, 0 otherwise; 32% of the paddy cultivators acknowledged that they changed planting dates based on the advice received through digital extension services, and 68% did not.		
Creation of bunds	The variables describe whether farmers created bunds or not: dummy = 1 if they did, 0 otherwise; 53% of the paddy cultivators acknowledged that they created bunds based on the advice received through digital extension services, and 47% did not.		
High-yielding variety seeds	The variables describe whether farmers used high-yielding variety seeds or not: dummy = 1 if they did, 0 otherwise; 69% of the paddy cultivators acknowledged using high-yielding variety seeds based on the advice received through digital extension services, and 31% of them did not.		

Source: Authors' computation.

4. RESULTS AND DISCUSSION

4.1 Efficiency Analysis

The efficiency scores presented in Table 2 show that more than 80% of the paddy cultivators had a low level of farming efficiency in the region. The overall technical efficiency of the paddy cultivators varied from 0.02 to 1, with a mean efficiency score of 0.14, which represents acute inefficiency in input resource utilization. The current study has undertaken in a tribal community of the state, where the farming is conducted with low-intensity input use and in fragmented land size settings. Hence, this lower level of farm efficiency compared to the national average is not surprising. The study area is one of the most backward regions in the state and has low sociodemographic indicators (Khosla and Jena 2020).

Only 4.5% of the total number of sampled farmers have achieved optimal pure technical efficiency, which is a measure of farm management efficiency and estimated using the VRS condition.¹ The majority of the respondents, i.e., 72%, are in a range between 0 and 0.4, which reveals that the farm management practices used in the study region need substantial upgrading. The second component of the overall technical efficiency, i.e., scale efficiency, reflects the state of scale of production, which is a function of the agricultural technology used. The scale efficiency measures the economies or the diseconomies of scale in farm cultivation. This score shows that 11% of the respondents have achieved optimal scale efficiency, leaving about 61% of respondents in the range between 0 and 0.4 of scale efficiency. This analysis reinforces the common phenomenon of low-intensity, low-technology agricultural production systems among small and marginal farmers in India.

Table 2: Estimated Results of Different Efficiency Measures

Efficiency Level	Overall Technical Efficiency	Pure Technical Efficiency	Scale Efficiency
Mean	0.14	0.35	0.41
S.D.	0.13	0.21	0.24
% of respondents between 0 and 0.2	81	28	17
% of respondents between 0.2 and 0.4	15	44	44
% of respondents between 0.4 and 0.6	2.9	14	17
% of respondents between 0.6 and 0.8	0.8	9.5	11
% of respondents between 0.8 and 1.0	0.3	4.5	11
Sample size	513	513	513

Table 3 presents a comparative analysis of efficiency scores between adopters and nonadopters of digital extension. The average overall technical efficiency among adopters of digital extension is 0.14, with a standard deviation of 0.14. Notably, nonadopters have a similar mean efficiency of 0.14, with a slightly lower standard deviation of 0.12, indicating a lower level of variability in this group. Nonadopters exhibit a mean pure technical efficiency of 0.39, with a standard deviation of 0.23, while adopters show a slightly lower mean of 0.32, with a standard deviation of 0.19.

¹ The VRS stands for Variable Returns to Scale, is used in Data Envelopment Analysis (DEA) to measure the efficiency of decision-making units (such as farms) while allowing for variable returns to scale. This condition assumes that efficiency can vary depending on the scale of operations, meaning that farms of different sizes can have different efficiencies.

Conversely, adopters demonstrate a mean scale efficiency of 0.44, with a standard deviation of 0.25, whereas nonadopters display a somewhat lower mean of 0.38, with a standard deviation of 0.23, suggesting a greater capability to optimize resources. Given their experience with digital technologies, adopters may be better able to maximize output creation and resource usage, as indicated by their higher mean efficiencies. While the narrower SD values among nonadopters may represent a more stable performance landscape in the absence of digital tools, the wider SD values among adopters may suggest differing degrees of organizational preparation or technological integration. These findings highlight the complex relationship that exists between the use of digital technology and efficiency outcomes in agricultural settings.

Table 3: Different Efficiency Scores With and Without Access to Telecommunication-based Extension Services (TES)

Efficiency Level	Adopters of TES			Nonadopters of TES		
	Overall Technical Efficiency	Pure Technical Efficiency	Scale Efficiency	Overall Technical Efficiency	Pure Technical Efficiency	Scale Efficiency
1	2	4	15	0	4	9
0.6–1	4	28	60	3	44	30
0.4–0.6	8	33	53	6	38	34
0–0.4	275	224	161	215	138	151
Minimum	0.02	0.15	0.12	0.02	0.13	0.12
Maximum	1.00	1.00	1.00	0.79	1.00	1.00
Mean	0.14	0.32	0.44	0.14	0.39	0.38
SD	0.14	0.19	0.25	0.12	0.23	0.23
Total Number of Farmers	289	289	289	224	224	224

Source: Authors' computation.

4.2 Determinants of Adoption of Telecommunication-based Extension Services (TES)

Table 4 presents the results of the probit model analyzing the determinants of accessing digital extension services. TES include call-based and SMS-based services adopted by farmers to seek information on improving agriculture productivity and technology adoption. The Wald chi-square test statistic (35.55) indicates that the explanatory variables are jointly statistically significant ($p < 0.1$). Education is considered to be the major determinant of access to digital extension services. Farmers with higher levels of education are more likely to use digital extension than farmers with lower levels. The age of farmers is another explanatory variable usually used in the literature as a determinant of accessing digital extension services. The coefficient of age was positive and significant, which indicates that the greater the age of farmers, the more likely they are to access digital extension. The negative and significant influence of secondary household income with access to digital extension indicates the notion that wealthier farmers are usually reluctant to use these services. Alcohol and cigarettes are psychoactive substances that influence the individual decision-making process and work performance (Hashemi et al. 2022). The results from the current study demonstrated that farmers consuming alcohol, cigarettes, and other psychoactive substances are unwilling to seek support from digital extension services. The results from the study found that the area under cultivation has a negative and significant impact on accessing information and knowledge from extension services. In addition, the coefficients of area, distance to seed/fertilizer

markets, and family size were statistically insignificant, suggesting no significant relationship in the usage of extension services. However, a negative and significant relationship was found between farming experience and digital extension. Individuals engaged in farming activity over a period of time are reluctant to use digital extension. Large-scale farmers, distance to seed/fertilizer markets, and family size of the household were found to be insignificant determinants in utilizing the knowledge and resources from digital extension services. Farmers availing themselves of TES indicated that mobile phones have tackled the challenges of traditional extension services by reaching millions of individuals and the remotest villages at negligible cost. TES have tried to fill the gap in information transformation. Farmers note that there exists a challenge for personalized extension services and also in-person demonstrations that were part of traditional extension activity.

Table 4: Probit Model Estimates of Determinants of Telecommunication-based Extension Services (TES) Adoption

Variable	Coefficient
Education	0.052*** (0.016)
Age	0.020** (0.008)
Secondary income diversification	-0.378*** (0.132)
Smoking or drinking	-0.273** (0.119)
Farming experience	-0.017** (0.008)
Area	-0.101 (0.095)
Distance to seed/fertilizer market	0.001 (0.009)
Family size	0.036 (0.034)
Constant	-0.421 (0.334)
Log likelihood	-333.58
Wald chi-square	35.55
Prob > chi-square	0.000

Note: *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Table 5 presents the average treatment effect on treated (ATT) and average treatment effect on untreated (ATU) of the intervention, i.e., having access to digital extension services. The full ESR results are shown in Appendix 1.3. The ATT results indicate that paddy cultivators using TES had mixed effects on the efficiency scores. There is no statistical difference in the estimated mean overall technical efficiency scores between the adopters of TES and counterfactual. The counterfactual in this case is: If the adopters had not adopted, what would have been their mean efficiency scores. The adopters have a mean efficiency score of 0.144 whereas the counterfactual group has a mean efficiency score of 0.146. This finding indicates that the adoption of digital extension has no noticeable impact on technical efficiency. Although this finding is in contrast to our theoretical hypothesis, similar insignificant impacts of mobile phones on smallholder farmers' marketing decisions were found in India (Fafchamps and Minten 2012).

Conversely, the comparison between non-adopters of TES and the counterfactual has revealed a statistically significant negative average treatment effect of non-adoption. Nonadopters of digital extension obtained a mean technical efficiency score of 0.137 whereas their mean technical efficiency had they adopted TES would have been 0.151 and the difference between these two mean scores is statistically significant. This finding has a mixed implication for the impact of digital extension adoption on farm efficiency as we could not get clear evidence of it from the empirical analysis. However, since the average treatment effect on nonadopters shows that these farmers could have achieved greater efficiency had they adopted digital extension, this is an indication that it might have a role in augmenting the overall extension process.

Table 5: Mean Treatment Effect of Access to TES

	Access	No Access	Average Treatment Effect
Access to TES	A: 0.144 (0.002)	C: 0.146 (0.002)	−0.002 (0.002)
No Access to TES	D: 0.151 (0.003)	B: 0.137 (0.002)	0.014*** (0.004)

Note: *** denotes significance at 1% level.

4.3 Estimates of TES on CSA Adoption

In this section, the study estimates the factors that determine the uptake of CSA technologies by farming households in the tribal region of Odisha. The four CSA technologies, namely farmyard manure (FYM), change in planting dates, soil conservation through the creation of field bunds, and high-yielding variety seeds, are used as the outcome variables. We model each outcome with two different specifications: Model 1 with the binary digital extension access variable along with other covariates, and Model 2 with the frequency of digital extension (the number of times farmers used TES in a crop cultivating season) along with other covariates but excluding the binary digital extension access.

Disaggregating the results by different technologies from Table 6, the study reveals that access to TES resulted in a higher uptake of CSA technologies such as rescheduling the planting dates, soil conservation, and high-yielding variety seeds. Further, we estimate the impact of the frequency (number of times an extension service is used) on the technology uptake. The effect of an increased frequency of extension services received through digital extension is more likely to influence the decision to adopt the same three technologies. Intuitively, crop-specific technology adoption may vary; the current study focused on the adoption of technologies in rice cultivation. The other covariate used in the estimation, namely the education level of the household head, is significantly associated only with soil conservation and was not found to be associated with other CSA technologies. Similarly, the age of the household head did not have any significant influence on the uptake of technology (significant only for rescheduling of planting dates). The coefficients of the covariate distance to the seed/fertilizer market negatively affected the adoption of CSA technologies. This indicates that a greater distance to the input market discourages technology adoption.

Table 6: Estimates of Effects of TES on Technology Adoption

	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Variable	FYM	FYM	Change in Planting Dates	Change in Planting Dates	Soil Conservation	Soil Conservation	H-Y Variety Seeds	H-Y Variety Seeds
Access to digital extension	-0.12 (0.27)		1.49*** (0.22)		1.01*** (0.18)		0.37** (0.19)	
Digital extension frequency		-0.06 (0.04)		0.11*** (0.03)		0.14*** (0.03)		0.08** (0.04)
Age	-0.006 (0.18)	-0.009 (0.01)	0.03*** (0.01)	0.04*** (0.01)	0.009 (0.01)	0.01 (0.01)	0.005 (0.01)	0.008 (0.01)
Education	0.006 (0.37)	0.009 (0.03)	-0.02 (0.02)	-0.001 (0.02)	0.02 (0.02)	0.03 (0.02)	-0.013 (0.02)	-0.012 (0.02)
Farming experience	0.03 (0.02)	0.03 (0.02)	-0.03*** (0.01)	-0.05*** (0.01)	-0.02* (0.01)	-0.03* (0.01)	-0.009 (0.014)	-0.013 (0.014)
Distance to seed/fertilizer market	-0.10*** (0.01)	-0.10*** (0.01)	-0.001 (0.01)	-0.004 (0.01)	0.01 (0.01)	0.01 (0.01)	-0.062*** (0.015)	-0.06*** (0.015)
Constant	2.89*** (0.73)	2.98*** (0.74)	-2.29*** (0.54)	-1.74*** (0.50)	-0.57 (0.47)	-0.3 (0.46)	1.32*** (0.51)	1.36*** (0.51)
Log likelihood	-182.27	-181.3	-288.87	307.89	-333.61	-339.87	-307.34	-306.77
Prob > chi-square	0.00	0.00	0.00	0.0001	0.00	0.00	0.003	0.002

Note: ***, **, and * denote significance at the 10%, 5%, and 1% level, respectively.

5. CONCLUSION

With a higher penetration of digital modes of communication in rural India, a technological boost has been received by the agriculture sector. A traditional bottleneck plaguing the development of the sector, i.e., the lack of effective extension services, can now be significantly reduced through digital extension services. The increasing usage by rural farmers of digital devices, especially mobile phones, has created an opportunity to use this facility to provide them with extension services digitally. The government of India, through its agricultural and meteorological departments, sends text and audio messages containing weather updates and information on the precise application of inputs and market prices of crops. The present study measures the impact of telecommunication-based extension services (TES) on the farmers of the tribal communities in eastern India.

The empirical results show that there is no unequivocal impact of digital extension on farm efficiency. It could not be empirically established that the adoption of digital extension has improved farm efficiency. This finding needs to be interpreted in the context of the study region, which is predominantly a tribal community of the country. The level of education is low, and the lack of skills required to understand the information provided digitally and translate it into action makes life difficult for the farmers of these communities. The focus group discussions we conducted with groups of farmers in some of the study villages revealed that the respondents still consider in-person interaction with village-level agriculture workers to be the most effective extension service. The farmers believe that knowledge of modern farming techniques can be communicated more effectively through in-person interaction with local agriculture extension workers. However, this kind of detailed in-person communication service is limited to those villages that are located close to urban areas. In addition, there is a shortage of village-level extension workers, with the ratio of extension workers to the villages under their jurisdiction being acutely inadequate, causing a low level of extension penetration. Furthermore, the logistical infrastructure needed to reach out to small and marginal farmers dwelling in remote rural areas is inadequate, leading to limited access to extension services, thereby creating challenges in dealing

with uncertain risks. It is in this context that the role of digital extension becomes crucial, so that there is a scope for digital services to contribute to agriculture development.

The study observed that farmers who adopted TES and used them more frequently were more likely to implement climate-smart agricultural practices. Therefore, it is crucial to enhance the effectiveness of TES within farming communities. To overcome the challenge of limited digital infrastructure, a substantial increase in call-in services and communication centers is necessary to make TES a viable option for agriculture. While message-based agricultural information can be relevant, organizing digitally curated solutions is essential. Additionally, the government must establish the knowledge and infrastructure needed to expand TES. It is also important to study farmers' willingness to pay for TES to ensure it becomes an effective intervention within the agricultural value chain.

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