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Digital Inclusion and Rural Agricultural Development: Socioeconomic Determinants of Mobile Phone–Based Information Use and Tomato Productivity in Bangladesh

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Mobile phone, Agricultural information, Technology adoption, Tomato production, Logistic regression, Bangladesh

ABSTRACT: Despite the growing push to bring mobile phones to smallholder farmers for access to crop information, there is limited evidence for productivity gains for high-value crops. This study aims to determine the constraints of informative mobile phone usage and its impact on tomato output from 200 tomato farmers of Noakhali Sadar in Bangladesh through a survey. Structured interviews were used to gather the data, which were then analysed using a Cobb–Douglas production function and OLS estimation as well as logistic regression. Education, credit access, group membership, household income and market distance had significant positive influence on the likelihood of informative mobile phone use ($p < 0.05$). Yield was significantly higher ($p < 0.01$) in informative use, land being under tomato crop and extension contact and lower in higher seed cost. Pest management, cost savings and timely farm operations were major advantages, and weak government support and limited credit availability were major constraints reported by farmers. There are opportunities to increase digital literacy, rural credit, and extension services to improve the effectiveness of agricultural advisory services delivered via mobile.

1. Introduction

Tomato (Solanum lycopersicum) is one of the most important crops in Bangladesh vegetable industry (Sharma et al., 2023). It provides Vitamins A, C and K and

lycopene, an antioxidant (Raza et al., 2022) and it has become a real cash crop for smallholders with the increased availability of off-season high yielding varieties (Das & Jahan, 2022) developed by the Bangladesh Agricultural Research Institute (BARI) and Bangladesh Institute of Nuclear Agriculture (BINA) (Bipu et al., 2026; Das & Jahan, 2022) Today, exports are to over sixty countries and if well managed, tomato is one of the more lucrative crops that a smallholder can produce (Hasan et al., 2020; Mitra & Sharmin, 2019). The problem of every crops in Bangladesh is that getting the management right requires farmers to have timely and accurate information regarding inputs, pests, disease and market conditions etc. (Rabbani and Ahmad, 2021; Ali et al., 2024)

Despite the fact that Bangladesh is an affluent country, rural livelihoods are still dependent on agriculture (Ahmad et al., 2026; Yeasmin et al., 2025) as the main source of income for most of the people (Khanom et al., 2023; Tusher etal., 2025) and a significant contribution to the national Gross Domestic Product (BBS, 2023). But information regarding that agriculture moves more or less by informal ways—a neighboring farmer, a local trader and word of mouth (Selim et al., 2026). Mobile phones are one of the few tools that can bridge this gap at scale (Ahmad et al., 2024; Selim et al., 2026). Weather forecast, pest alert, and market prices are now available to the farmers at their fingertips through the Department of Agricultural Extension's Krishi Batayan portal and helpline 16123 as well as SMS and call-based services from service providers such as Grameenphone, Robi, and Banglalink (Ahmed & Sultana, 2021; BTRC, 2022). Farmers also look at other informal sources for information on farming such as Facebook, YouTube etc. (Mamun-ur-Rashid et al., 2019).

Despite the agro-climatic suitability and the close proximity to tomato markets, tomato is also an important crop of Noakhali District which faces high pest pressure and low production technology and knowledge, irregular rainfall, and late and poor market information, all of which are increasing the production cost and lowering the yield (Haque et al., 2020; Uddin et al., 2018; Islam et al., 2019). In theory, a mobile phone could solve a number of these issues simultaneously (Hasan et al., 2026; Fawwad et al., 2026). In reality, farmers' cell phone usage varies widely, with some only using phones for calls and others seeking out weather forecasts, pest warnings, and price lists. It remains to be seen if there is any systematic relationship between this difference in use, as opposed to ownership alone, and farmers' socio-economic characteristics and if this difference is reflected in the numbers at harvest in the case of Bangladesh's tomato growers.

This study aims to answer that question by three objectives: determine what factors predict use of mobile phones for information among tomato farmers, estimate the value of that use in the context of tomato crop output, and capture the advantages and concerns farmers have regarding mobile phone use for information and what could alleviate those concerns. The analysis takes place on three questions. What factors influence informative use of mobile phone amongst tomato farmers? Are there real differences between the yield of informative and non-informative users with tomato? So, what is blocking the way to more value from mobile-based information and how could that be solved? The answers are for those extension agencies, mobile network operators, and policy makers who are working to create an advisory service that extends to the farmers, in practice, not in principle.

2. Literature Review

By now, the potential of mobile phones for agricultural benefit in developing countries has a quite solid evidence base. Aker (2010) was ahead of the curve: grain price dispersion across markets declined as mobile phone coverage became more available, albeit unevenly, across Niger, and so did traders' search costs. The same author in another follow-up study broadened his scope and contended that while ICTs can, on average, reduce information asymmetries between farmers and extension providers, the extent of adoption remains constrained by the level of farmer's access to ICTs and the design of the services (Aker, 2011). The trend continues elsewhere. Mobile-based advisories had a positive impact on maize producers in Tanzania, who reported market management benefits, as well as increased yields and large-scale adoption of advisories (Kisena & Kwesigabo, 2023); in Kenya, knowledge of and use of the ICT-based market information services depended on who the farmer was, who they were accessible to and who they were located with, with real benefits reported in terms of reduced transaction costs and a stronger bargaining position for the farmer (Okello et al., 2014). In Nepal and Zimbabwe, age and education, however, continued to be the most significant factors influencing the use of mobile Apps for agro-advisory functions in scenarios where almost everyone possessed a mobile phone (Tiwari et al., 2024; Mabika et al., 2025).

Similarly, the same story can be seen in the context of Bangladesh-specific work, but with local flavor. Islam and Grönlund (2011) developed a Rural Technology Acceptance Model based on Bangladeshi farmers, and identified perceived usefulness and social influence as drivers of adoption, while the cost of the technology and overall fear of digital services were barriers to adoption. In his study with 110 farmers, Rahman et al., 2018 identified that farmer's frequency of calls to extension officers

was influenced by education, farm size, household income and prior extension contact where a substantial proportion of farmers did not call extension officers at all. In addition to mobile phones specifically, the studies on television, radio and rural information center indicate the same trend, with low literacy, weak infrastructure and thin extension staffing emerging as the recurring problems as well as barriers to the adoption of ICT exposure to improve farming knowledge (Chowhan & Ghosh, 2020; Hasan et al., 2019; Ahsan et al., 2022; Tanvir & Bhattacharjee, 2024).

There are few studies that make a direct link with the information flow and what is happening in the field. Kumar et al. (2020) reported that hydroclimatic forecasts were the most valued type of information by farmers in the lower Bengal Delta, while Rahman et al. (2023) demonstrated that reasonably good prediction of the harvest outcome in Bangladesh was possible using automated, sensor-based monitoring. The most similar to the current work is Ahmad et al. (2024), which showed positive correlation of the use of mobile phones and the production of Boro rice in the Eastern Gangetic Plain with education, household income, credit access, and extension contact as predictors, all of which are also tested here but in a much more perishable and management-intensive crop than rice. So far, tomato research in Bangladesh has been conducted on parallel tracks: value-chain research has identified favourable benefit-cost ratios for tomato cultivation (Bipu et al., 2025), and a survey of 10 districts found that the majority of tomato growers have been impacted by pests and diseases, often without receiving formal training on prevention or treatment (Hossain et al., 2025). There is a gender dimension that is important to note: Bangladeshi smallholders with mobile phones are more likely to be meaningfully connected with higher yields and farm profit; however, women are less likely to be meaningfully connected, likely due to literacy and affordability gaps (Kandulu et al., 2025); this is similar to other evidence globally that suggests the need for deliberate and targeted programming to bridge the agriculture's ICT gender gap (FAO, 2023).

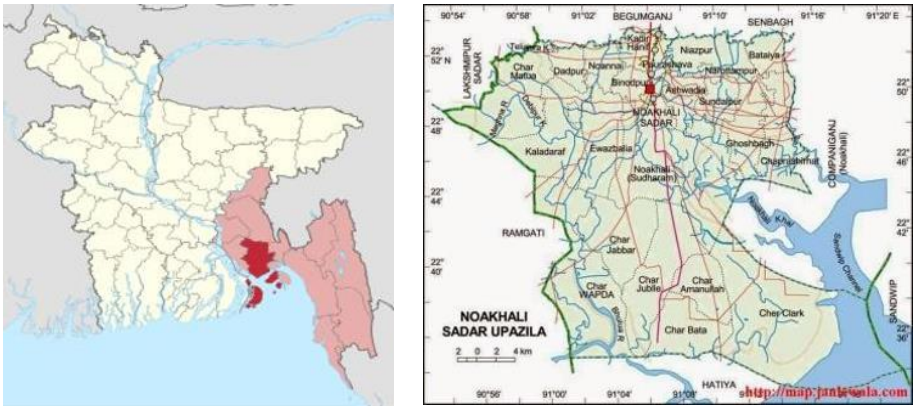
Combined, the overall picture emerging from this literature is that mobile phones can enhance information flows and, at least sometimes, farm outcomes and that the differences between those who adopt and those who do not lie in the education, income, credit access and institutional support they receive. What it hasn't done, though, is single out informative use, as opposed to simple ownership or general use, and pose the question: Does this distinction matter for tomato growers, in particular, since the price fluctuations, pest exposure and short cropping cycle of tomatoes make timely information particularly important? However, the literature from Bangladesh has focused on profit or pest knowledge, not both, and seldom considered the mobile

as a medium of information, while the literature on the mobile has been in the field of cereals and value chains rather than tomato production. This paper falls in between those two literatures where there is still a gap, and thus, in this paper, I have tried to model the determinants of informative mobile phone use and the yield effect together, for tomato growers in Noakhali Sadar.

3. Materials and Methods

3.1 Study Area

The fieldwork was carried out in Noakhali Sadar Upazila in Noakhali District in the southern coast of Bangladesh (Figure 1). Not every choice was inevitable: The upazila is one of the better tomato-growing regions in the coastal belt, with fertile alluvial soil and a farming population that is increasingly reliant on mobile phones for farming advice as well as for access to markets. It consists of 1 municipality and 13 unions, and has a population of approximately 331,493 (BBS, 2023) of which 49.15 percent are employed in agriculture and about 56.3 percent of households are landholders while the remaining ones are landless. Considering the economic significance of tomato, paddy, pulses and sugarcane, and the strong local market dynamics, the upazila was a natural choice for the study on the impact of mobile information on farming decisions.



(a) *(b)*

Figure 1. Location of the study area: (a) Noakhali District within Bangladesh; (b) Noakhali Sadar Upazila

Source: (a) adapted from Wikimedia Commons administrative map of Bangladesh; (b) Banglapedia / map.jantrala.

3.2 Sampling and Data Collection

Two hundred tomato farmers were selected in two stage random sampling. In the villages of Noakhali Sadar, the farmers were randomly selected from the purposefully selected villages considering the tomato growing level of the villages and the questionnaire were collected from the household head or other major farm decision maker. The instrument itself was written in Bengali in five modules – general and socio-economic information, farm characteristics, mobile phone use and information access, perceived benefits and barriers, and support services received, and was tested with a pilot round prior to full deployment to iron out any ambiguity in the wording. The face-to-face interviews were conducted by six trained enumerators from 30th August to 15th September 2025.

3.3 Perception Index

Benefits and barriers associated with mobile-based agricultural information were captured on a three-point scale (agree, neutral, disagree), following the approach set out by Malhotra (2007); Burns and Burns (2008) and Ali et al., (2024). Responses to each statement were then converted into a single Perception Index (PI):

$PI = 3A + 2D + 1N$

Here A, D, and N denote how many respondents agreed, disagreed, or stayed neutral on a given statement. Ranking statements by their PI score puts the ones with the strongest overall agreement at the top (Ahmad et al., 2022).

3.4 Analytical Framework

Two econometric models do the work of answering the study's questions. The first is a binary logistic regression that isolates what predicts informative mobile phone use — defined here as actively using a phone to obtain weather, pest and disease, market price, or other farming-related information (coded 1), as against non-informative or no use at all (coded 0). The log-odds of informative use are written as a linear function of farmer and household characteristics:

$$\ln[P_i/(1-P_i)] = \beta_0 + \beta_1(Age) + \beta_2(Education) + \beta_3(Marital\ status) + \beta_4(Household\ size) + \beta_5(Access\ to\ credit) + \beta_6(Membership) + \beta_7(Dependents) + \beta_8(Income) + \beta_9(Market\ distance) + \varepsilon_i$$

where P_i is the probability that farmer i uses a mobile phone informatively, β_0 is the intercept, β_1–β_9 are coefficients to be estimated, and ε_i is the stochastic error term.

The second model estimates what informative mobile phone use is worth in terms of tomato yield, using a Cobb-Douglas production function in log-linear form (Islam et al., 2026). It follows the general specification laid out by Antle (1983) and the Hicks-

neutral technical-change framework (Sato, 1970; Wood & Woods, 1989): $ln\ Y_i = ln\ A_i + \alpha\ ln\ T_i + \beta\ ln\ L_i + \delta\ ln\ K_i + \varepsilon_i$

In this model Yi represents tomato production per farmer and Ai is a Hicks-neutral technology parameter, which in this study is interpreted as the use of a mobile phone for informative purposes. The production factors are seed, fertilizer, etc. (Ti), labour (Li) and physical capital (Ki) -cultivated land etc. First, following Houghton (2009), mobile phone use was modelled separately from other non-informative uses of the mobile phone including entertainment or simply social contacts; then, the predicted value from this first-stage logit model was included in the production function as the main regressor of interest, together with seed cost, tomato-cultivated land, farming experience, farm type, family labour, training and extension contact, and the dependent variable was tomato yield. This way of breaking down the estimation separates what productivity increases are due to informative use and what productivity increases are due to having or using a phone at all.

Multicollinearity among the explanatory variables was tested before the estimation process using variance inflation factor (VIF) which are highly correlated regressors may generate biased estimates of the coefficient and the standard errors of the parameters if they are not treated (Alin, 2010; Daoud, 2018; Ahmad et al., 2022) and the result of the test was reported in Table 6. Robust standard errors were used throughout both models to guard against heteroscedasticity (Gujarati et al., 2012) and the area under the receiver operating characteristic (ROC) curve (Figure 5) was used to test whether or not the logit model was able to discriminate between the informative users and the non-informative users. All estimation was done in Stata MP 16.

4. Results and Discussion

4.1 Socio-demographic and Farm Characteristics

The socio-demographic and farm profile of the 200 sample tomato farmers are presented in tables 1 and 2 respectively. The average age of the respondents was 47 years, most being in the age group 30-60 and relatively few aged less than 30 years. This is expected given the sampling frame based on household heads, which is skewed towards males (82.5%) and married people (87.5%). Formal education was limited: 43.5 per cent of the respondents had no formal education and those who had an average of less than five years; but about one-quarter of them had completed their education up to SSC or HSC. Average household size was 5.5 persons and, while tomato farming was mainly done by men (78.0%), non-trivial 22.0 percent of farms was under female control. The size of the land holdings is very similar to the

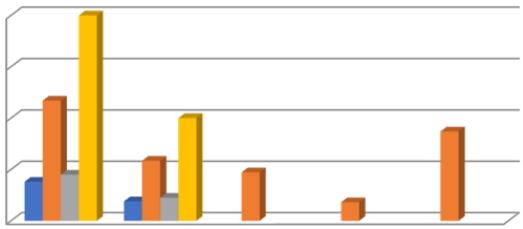
characteristics of a smallholder: on average, 0.57 hectares of land were owned and only 0.17 hectares of tomato cultivated, with two-thirds of households at the low end of the 3-month income spectrum. Access to markets was moderate (7.4 km on average) while the average farmer owned a mobile phone for 11 years, with half of these using basic (button) phones and the remaining half smartphones; contact with agricultural extension services was low, and averaged less than one visit per season. This combination will result in the determinants analysis in Section 4.3: older, mostly male, land poor, largely outside the reach of extension services.

Table 1. Descriptive Statistics of Continuous Variables for Sample Tomato Farmers (N = 200)

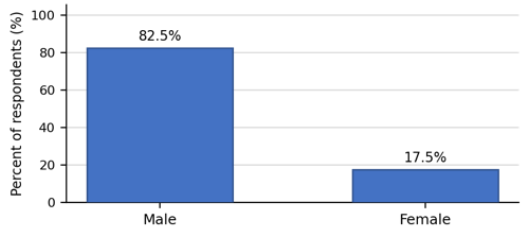
Variable / Category	Freq.	%	Mean	Min	Max
Age (years)			**47.12**	**18**	**87**
18–30	38	19.0			
>30–60	117	58.5			
>60	45	22.5			
Farmer's education (completed years of schooling)			**4.35**	**0**	**12**
No formal education	87	43.5			
Read & write only	1	0.5			
Primary (Grade 1–5)	61	30.5			
Secondary (SSC)	25	12.5			
Higher secondary (HSC)	26	13.0			
Household size (members)			**5.50**	**2**	**13**
2–4	78	39.0			
>4–8	98	49.0			
>8	24	12.0			
Farming experience (years)			**20.71**	**2**	**55**
≤10	58	29.0			
>10–20	50	25.0			
>20–30	51	25.5			
>30	41	20.5			
Family members engaged in farming (number)			**2.36**	**1**	**9**
1–4	178	89.0			
>4–9	22	11.0			
Total land owned (hectares)			**0.57**	**0.004**	**8.09**
≤1.00	193	96.5			

>1–2	5	2.5			
>2	2	1.0			
Land under tomato cultivation (hectares)			**0.17**	**0.001**	**2.23**
≤1.00	196	98.0			
>1	4	2.0			
Distance to nearest market (km)			**7.36**	**2**	**15**
≤5	79	39.5			
>5–10	87	43.5			
>10	34	17.0			
Duration of mobile phone use (years)			**11.15**	**2**	**20**
2–6	29	14.5			
>6–11	83	41.5			
>11–16	63	31.5			
>16	25	12.5			
Contact with extension services (visits/season)			**0.99**	**0**	**10**
≤2	170	85.0			
>2–5	29	14.5			
>5	1	0.5			

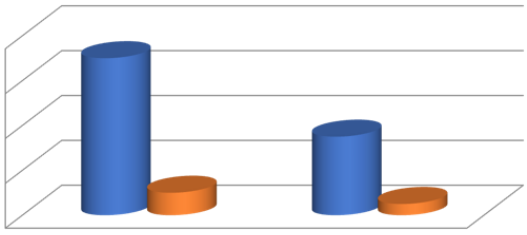
Source: Field survey, 2025.



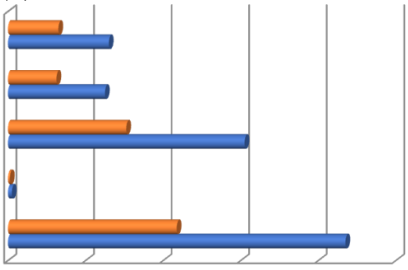
(a) Age (years)



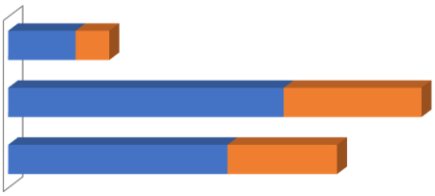
(b) Gender



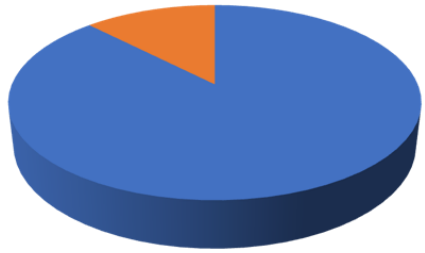
(c) Marital status



(d) Education

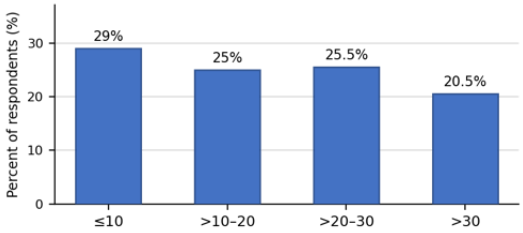


(e) Household size

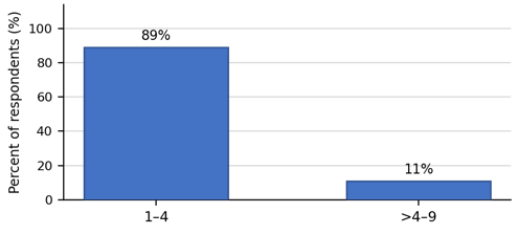


(f) Gender of primary farm operator

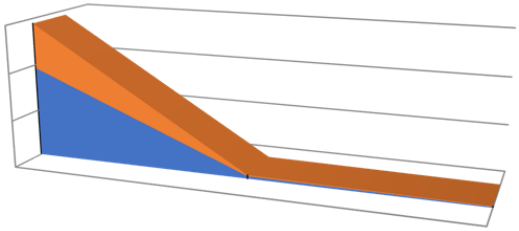
Figure 2. Socio-Demographic Characteristics of Sample Tomato Farmers: (A) Age, (B) Gender, (C) Marital Status, (D) Education, (E) Household Size, (F) Gender of the Household Member Primarily Engaged in Tomato Farming
Source: Field Survey, 2025.



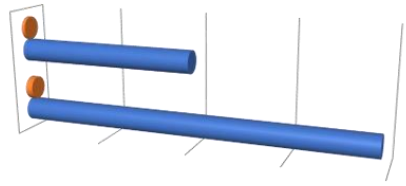
(a) Farming experience (years)



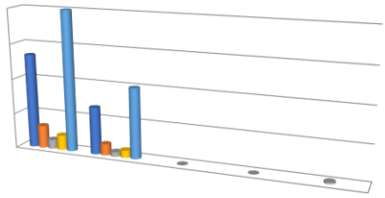
(b) Family members in farming



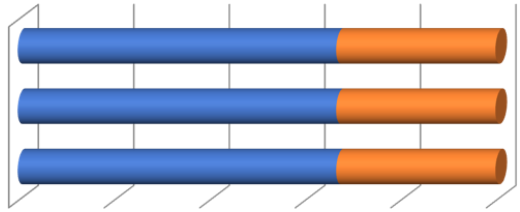
(c) Total land owned



(d) Land under tomato cultivation



(e) Household income (3-month)



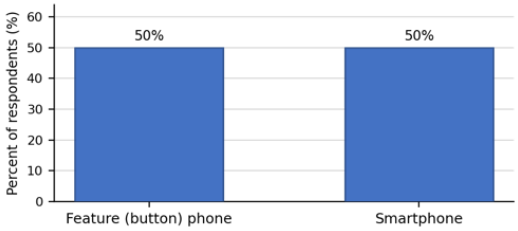
(f) Distance to nearest market

Figure 3. Farm and Economic Characteristics of Sample Tomato Farmers: (A) Farming Experience, (B) Family Members Engaged in Farming, (C) Total Land Owned, (D) Land Under Tomato Cultivation, (E) Household Income, (F) Distance to Nearest Market Source: Field Survey, 2025.

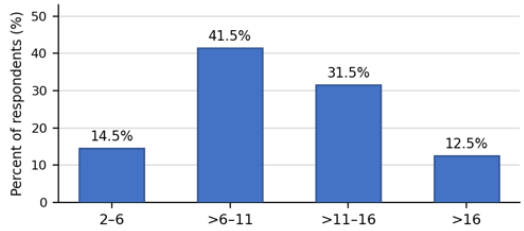
Table 2. Categorical Characteristics, Information Access, and Support Services (N = 200)

Variable	Distribution (%)
Gender	Male 82.5; Female 17.5
Marital status	Married 87.5; Single 12.5
Gender of primary household tomato farmer	Male 78.0; Female 22.0
Mobile phone type	Feature (button) phone 50.0; Smartphone 50.0
Household income, 3-month total ('000 BDT)	≤80: 67.0; >80–130: 16.0; >130–180: 6.5; >180: 10.5
Access to mobile-based agricultural information[a]	Yes 50.5; No 49.5
Farmers' organization / cooperative membership	Yes 28.0; No 72.0
Use of AI-based farming tools	Yes 49.5; No 50.5
Received training related to self-employment[b]	Yes 36.4; No 63.6
Perceived mobile phone use improved farm income	Yes 47.0; No 46.5; Not sure 6.5
Source of institutional support received	None 71.0; Semi-govt. 12.0; Non-govt. 10.5; Govt. 6.5

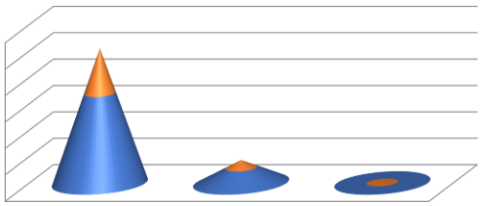
Source: Field survey, 2025. a Information types covered include weather updates, pest and disease control, market prices, seed selection, irrigation, and harvesting guidance, obtained through channels such as Facebook, YouTube, agricultural call centers or apps, NGOs, and government SMS services. b Training question answered by 198 of 200 respondents.



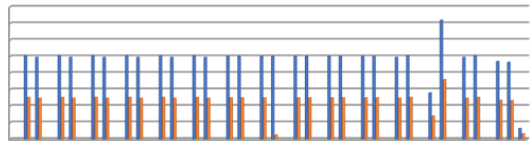
(a) Mobile phone type



(b) Duration of mobile phone use



(c) Extension service contact



(d) Type of agricultural information accessed

Figure 4. Mobile phone use and information access among sample tomato farmers: (a) mobile phone type, (b) duration of mobile phone use, (c) extension service contact frequency, (d) type of agricultural information accessed via mobile phone
Source: Field survey, 2025.

4.2 Access to Information and Farmers' Perceptions

Approximately half of the respondents indicated that they received any of the types of agricultural information requested by the survey on mobile devices, indicating that access to agricultural information is still not universal and that no single source has emerged as the predominant source (Table 2). Organizational membership was rather low (28.0 percent), as was the use of AI-powered farming tools (49.5 percent), and only 36.4 percent of farmers had undergone any self-employment or income diversification-related training. There was a near split (47.0% yes to 46.5% no) on the question of whether the use of mobile phones had actually contributed to an improvement in the income of the farmers. Overall, institutional support proved low: 71.0 percent of farmers reported receiving no support from either government or non-government/semi-government organizations; and when support was received, it was most likely to come from semi-government institutions, mostly banks.

From the farmers' perspective, mobile-based information offers the best benefit with better pest management (PI = 476), reduced production cost (PI = 475), and improved timing of farm operations (PI = 465) compared to increased yield (PI = 421) and higher market prices (PI = 365) (Table 3, Panel A). That ordering implies something – farmers are utilizing mobile information more as a day-to-day tool (when to spray a pesticide, when to do a task) than in a way that drives the price they receive. The barriers have a corresponding story (Table 3, Panel B). Weak government support is the largest constraint (PI = 540), followed by limited credit access coupled with high input costs and volatile price (PI = 512) and shortages of quality seed, water and technical help (PI = 510); soil and irrigation problems (PI = 501) and poor storage coupled with middlemen (PI = 467) come next. None of the top three barriers is actually related to technology — they're institutional and financial and that means that

disseminating more mobile advisory content alone will get us a long way, but not very far without investment in credit, input markets and public extension.

Table 3. Farmers' Perceptions of the Benefits and Barriers of Mobile-Based Agricultural Information, Ranked by Perception Index (PI)

Statement	Agree	Disagree	Neutral	PI	Rank
Panel A. Perceived benefits of mobile-based agricultural information					
Better pest management	297	156	23	476	1
Reduced production cost	291	162	22	475	2
Improved timing of farm operations	285	150	30	465	3
Increased yield	273	78	70	421	4
Higher market prices	180	150	35	365	5
Panel B. Barriers to mobile-based agricultural information use					
Inadequate government support	510	10	20	540	1
Lack of credit, high input cost, price fluctuation	438	40	34	512	2
Shortage of quality seed, water, and technical knowledge	432	44	34	510	3
Soil and irrigation constraints	423	38	40	501	4
Poor storage and middlemen dominance	375	34	58	467	5

Source: Field survey, 2025. Agree, Disagree, and Neutral columns show the number of respondents in each response category weighted by 3, 2, and 1 respectively (Section 3.3); columns sum to PI. n = 200 per statement.

4.3 Determinants of Informative Mobile Phone Use

The results of the logistic regression analysis for the prediction of informative use of mobile phone are presented in Table 4. The model fits well (pseudo $R^2 = 0.721$; LR $\chi^2(9) = 108.61$, $p < 0.001$) and is able to effectively separate informative from non-informative users about as cleanly as a model can (area under the ROC curve = 0.973). One significant and positive result relates to education: better educated farmers are just better able to identify the value of information and to synthesize the information they receive from their mobile devices on weather, prices, and crop management. Organizational membership and household income are each significant at the 5 percent level as well, which is consistent with a narrative that financial flexibility and access to peer or cooperative networks facilitates the search for information more than other factors, but that the cost of data or airtime remains important for poorer households. Among the significant variables, the one that has the greatest effect is

distance from the nearest market ($p < 0.01$): people living further away are more likely to use their phones in an informed fashion as if the phone were a substitute for an ability to access prices and markets that would otherwise be expensive. The basic demographics (age, marital status, household size, number of dependents) are not significant - once education, income, credit and market distance are included, these variables do not add much.

Table 4. Logistic Regression Estimates of the Determinants of Informative Mobile Phone Use

Variable	Coefficient	Robust S.E.	z	p-value
Age	0.553	1.189	0.47	0.642
Education	0.506***	0.188	2.69	0.007
Marital status	−0.048	0.137	−0.35	0.723
Household size	0.036	1.723	0.02	0.984
Access to credit	0.475**	0.235	2.02	0.043
Membership	0.458**	0.220	2.08	0.038
Number of dependents	−0.314	1.033	−0.30	0.761
Household income	1.681**	0.832	2.02	0.043
Distance to market	0.729***	0.282	2.58	0.010
Constant	10.540	11.374	0.93	0.354

*Note: Dependent variable = 1 if the farmer uses a mobile phone for informative (agricultural) purposes, 0 otherwise. N = 200; mean of dependent variable = 0.875; Pseudo $R^2 = 0.721$; LR $\chi^2(9) = 108.61$ ($p < 0.001$); AIC = 62.10; BIC = 95.08; AUC = 0.973. Robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

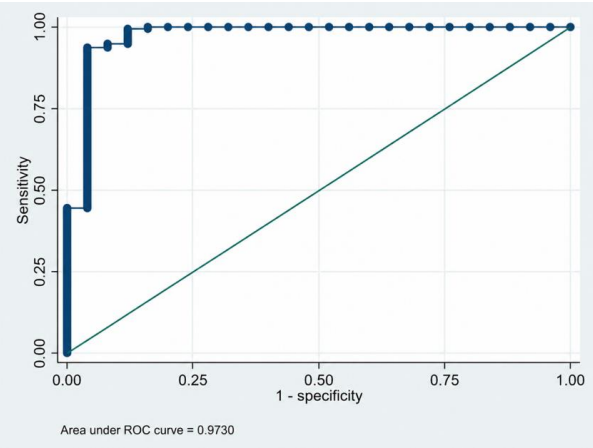


Figure 5. Receiver Operating Characteristic (ROC) Curve for the Logistic Regression Model (Area Under the Curve = 0.973)

4.4 Effect of Informative Mobile Phone Use on Tomato Yield

Table 5 carries the Cobb-Douglas estimates linking tomato yield to informative mobile phone use and the other production inputs ($R^2 = 0.527$; $F(9,190) = 23.51$, $p < 0.001$). Informative use comes out positive and significant ($p < 0.01$): holding everything else fixed, a one-unit rise in the predicted intensity of informative use tracks with roughly a 0.9 percent increase in tomato output, which fits farmers putting timely weather, pest, and market information to work in better-timed production decisions. Land under tomato cultivation and extension contact are the other two variables that come out strongly significant and positive (both $p < 0.01$), a reminder that farm scale and institutional support still matter alongside whatever the phone contributes. Seed cost, by contrast, carries a significant negative coefficient ($p < 0.01$). That is not evidence that better seed lowers yield — a more plausible read is that farmers spend more on seed precisely where growing conditions are already tougher, or that seed cost and seed quality do not track each other as closely as one would hope, a question that would need input-quality data to settle properly. Credit access, farming experience, farm type, family labor, and training all drop out as non-significant here, suggesting that on their own, none of them binds as tightly on yield as land, extension contact, and information use do for these farmers.

Table 5. OLS Estimates of the Cobb-Douglas Production Function for Tomato Yield

Variable	Coefficient	Robust S.E.	t	p-value
Informative mobile phone use (predicted)	0.009***	0.003	3.47	0.001
Access to credit	0.042	0.044	0.95	0.343
Seed cost	−0.016***	0.005	−3.18	0.002
Tomato-cultivated land	0.059***	0.009	6.89	0.000
Farming experience	0.008	0.042	0.19	0.851
Farm type	−0.003	0.003	−0.84	0.401
Family members in farming	0.012	0.026	0.45	0.653
Training	0.052	0.132	0.40	0.692
Extension services	0.025***	0.005	4.61	0.000
Constant	0.536*	0.298	1.80	0.073

*Note: Dependent variable = tomato yield. $N = 200$; $R^2 = 0.527$; $F(9,190) = 23.51$ ($p < 0.001$); AIC = −4.68; BIC = 28.30. Robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

4.5 Diagnostic Checks

Multicollinearity among the explanatory variables was checked formally with the variance inflation factor (VIF), following Alin (2010) and Daoud (2018) (Table 6). Every value comes in under the usual threshold of 10 (mean VIF = 3.33), so multicollinearity is not a material problem for either regression above; the two highest values — informative mobile phone use at 6.88 and access to credit at 6.36 — are still within an acceptable range, though they do point to some shared variation between those two variables worth keeping in mind when reading their individual coefficients. Robust, heteroscedasticity-consistent standard errors run through both Table 4 and Table 5 as a further safeguard given the cross-sectional nature of the sample.

Table 6. Variance Inflation Factors (VIF) for the Explanatory Variables

Variable	VIF	1/VIF
Informative mobile phone use (predicted)	6.876	0.145
Access to credit	6.364	0.157
Tomato-cultivated land	4.580	0.218
Total land owned	4.115	0.243
Duration of mobile phone use (years)	1.959	0.510
Education	1.856	0.539
Log of household income	1.771	0.565
Household size	1.402	0.713
Gender	1.047	0.955
Mean VIF	3.330	—

Source: Field survey, 2025. Rule of thumb: VIF > 10 indicates problematic multicollinearity.

Read together, these results line up with earlier work showing that mobile-based information helps smallholders make better decisions and produce more (Aker, 2010; Ahmad et al., 2024; Kandulu et al., 2025), and they extend that evidence to tomato specifically, a crop where timely pest and price information carries unusual weight. That informative use clusters among farmers who are already more educated, better connected, and linked to credit echoes what has been found for Bangladesh generally (Islam & Grönlund, 2011; Rahman et al., 2018), and it raises a real concern: without deliberate targeting, mobile advisory services risk mostly reaching farmers who were already reasonably well off to begin with. At the same time, the fact that market distance raises the odds of informative use hints that phones are already doing some of the work that physical market access would otherwise do, which is worth keeping in mind for extension planning in geographically spread-out coastal unions like Noakhali Sadar's.

5. Conclusion and Policy Recommendations

This paper set out to explain what drives informative mobile phone use among tomato farmers in Noakhali Sadar Upazila and to put a number on what that use is worth in tomato yield, drawing on survey data from 200 farmers. Education, credit access, group membership, household income, and distance from the nearest market all raised the odds that a farmer used a mobile phone informatively; age and household size, along with the other basic demographics, did not. Informative use itself came with significantly higher yield, alongside land under cultivation and extension contact, while higher seed cost pulled in the other direction. Farmers valued the technology most for pest management, lower costs, and better timing; what held them back most was weak government support and thin credit access.

A few policy implications follow. Because informative use concentrates among farmers who are already better educated and better resourced, digital and agricultural literacy programs aimed specifically at those currently left out would help keep mobile advisory services from widening gaps that already exist. Credit access mattered in both models, which points toward expanding rural credit and microfinance — possibly bundled with advisory subscriptions — as a way to loosen financial constraints and encourage information-seeking at the same time. Farmer cooperatives and organizational networks, shown here to go along with informative use, look like a workable channel for spreading mobile information further through peer contact. The link between market distance and informative use suggests extension agencies and network operators should push advisory coverage toward the more remote, poorly connected unions first, since phones already seem to be filling in for market access there. The seed cost finding points to something worth checking in the input market, possibly quality mismatches that mobile advisory content on seed selection could help flag. And because extension contact predicts yield on its own, independent of phone use, in-person extension capacity still needs investment: mobile information works alongside direct extension contact, not instead of it.

A few caveats apply. The cross-sectional design means these are associations rather than proven causal effects, and while the two-stage approach separates informative use from general phone use, something unobserved — a farmer's underlying drive or ability, say — could still be pulling both information-seeking and yield in the same direction. The sample covers one upazila and one crop, so how well this generalizes to other regions or crops with different market and infrastructure conditions remains an open question, and both yield and information use were self-reported, which brings the usual recall and social-desirability concerns along with it. A natural next step

would be panel data across several growing seasons, a larger and more geographically varied sample, and some direct measure of what the information actually contained and how good it was — all of which would help pin down the causal link between mobile phone use and farm productivity more firmly than a single cross-section can.

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