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Declaration of Conflict Interest
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors have reviewed and approved the final manuscript and confirm that there are no conflicts of

interest associated with this publication.

Ethical Approval

Ethical approval for this study was obtained from the Sher-e-Bangla Agricultural University Research System (SAURES), Sher-e-Bangla Agricultural University, Dhaka, Bangladesh. The study was reviewed and approved by the relevant institutional research ethics and scientific committee in accordance with university guidelines for research involving human participants. All procedures were conducted in compliance with institutional ethical standards and the principles of the Declaration of Helsinki.

Consent to Participate

Participation in the survey was voluntary, and informed consent was obtained from all respondents prior to data collection. Respondents were informed about the purpose of the study, confidentiality of their responses, and their right to withdraw at any stage without any consequences. No personally identifiable information was collected, and data were used exclusively for academic research purposes.

Clinical Trial Number

Not applicable

Consent for publication

Not applicable.

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Abstract

Farmers have an increasing need for financial resources, which has led to the development and adoption of Fintech. Fintech and climate-smart agricultural technologies might revolutionize how we fight climate change and promote sustainable farming, contributing to Sustainable Development Goal (SDG) 2 (Zero Hunger) and SDG 13 (Climate Action) by improving agricultural productivity and climate resilience. This research aims to identify the determinants of Fintech adoption and productivity of rice and maize cultivation, and how Fintech affects farmers' adoption of climate-smart agriculture technology in transforming the agro-economy. To evaluate the effect of Fintech on rice and maize production, the study carried out a cross-sectional survey in Kaliganj and Kaliakair Upazilas of Gazipur district of Bangladesh. In total, 240 rural households were selected for face-to-face interviews using a structured questionnaire. To achieve the study's goals, a binary logistic model and a Cobb-Douglas production function were used. bKash, Rocket, and Nagad are widely chosen Fintech technologies among the top six favorite Fintechs. Education, remittances, the number of mobile phones, fintech adoption, and family size significantly affect the adoption of climate-smart agricultural technologies for both rice and maize farmers. Both rice and maize output are significantly influenced by fertilizer use, family size, number of mobile phones, remittances, and the use of financial technology. Policymakers should strengthen rural financial infrastructure, encourage the adoption of Fintech and climate-smart agriculture, and prioritize digital literacy and financial awareness in line with SDG 9 (Industry, Innovation and Infrastructure), SDG 2, and SDG 13. Our research expands understanding of how Fintech activities affect CSA practices in rice and maize farmers, supporting decisions aligned with institutional and governmental goals for sustainable development.

Keywords: Fintech, Climate-Smart Agriculture (CSA), Adoption, Rice, Maize

JEL codes: D24, Q14, Q16, Q54

1. Introduction

Globally, 1.7 billion individuals, the majority of whom residein developing nations, lack access to basic financial services, thereby impeding their ability to overcome poverty [1]. The Asia-Pacific Fintech industry is projected to reach $150 billion by 2025. China and India ranked first and second, respectively, on the EY Global Fintech Adoption Index 2019, with scores of 87 percent and 87 percent. Bangladesh, a neighbor to both fastest-growing Fintech economies, is accelerating its embrace of Fintech byleveraging mobile technology, with a particular focus on mobile financial services [2]. Fintech has become a commonly used term to characterize technological innovations that have the potential to alter the delivery of financial services, stimulate the development of new business models, apps, processes, and products, and result in customer wins [3, 4, 5]. Financial technologies (Fintech) are fundamentally financial services enabled by revolutionary technological paradigms [6]. Fintech is a booming and innovative concept worldwide that refers to new technologies designed to enhance and automate the supply and use of financial services by businesses [2]. These technologies are utilized extensively by the financial institutions and banks of Bangladesh, such as bKash, Rocket, Nagad, mCash, Upay, Islamic Wallet etc. [7, 8]. It is one in which digital technologies enable innovative delivery of existing services and permit the developmentof new ones [7]. Customers around the world have begun to enjoy the benefits of innovative platforms and services. Using Fintech to promote financial inclusion across businesses and communities in Bangladesh is just half of the answer [9]. Fintech is one ofthe most significant breakthroughs in the financial services sector, and it is fueled by economic sharing, regulation, policy, and information technology. Fintech advances offer to give accessto financial services, including payments, savings, credit, and insurance for the underprivileged [10]. Therefore, Fintech may be described as an umbrella word for financial services and business models enabled by innovative technology [11].

CSATs provide opportunities to address climate change issues, as well as to support economic development and improve the agricultural industry [12]. Some of the well-known climate-smart agricultural technologies include the use of submergence-resistant, high-yielding varieties, solar-powered irrigation, salinity-resistant, proper use of fertilizer, direct seedlings, use of lodging-resistant (tall) varieties for rice farmers, conservation agriculture, intercropping with short-duration vegetables, alternate wetting and drying, and integrated soil fertility management for maize farmers [13].

The Fintech and CSA technology concepts are relatively new in the agricultural sector and not well understood and appreciated by policymakers, scientists and farmers in our country. Farmers may modify or combine Fintech with other practices and CSA technologies to addresstheir specific conditions and strategy. Previous studies [14, 15, 16, 17] have analyzed the impact of financial inclusion on poverty reduction and income inequality reduction in emerging countries, none of them have been conducted in Bangladesh's agricultural sector. There are several benefits to using financial institutions to mobilize private financing for climate smart agriculture, such as easier fund delivery, lower transaction costs, and increased reach among a wider range of farmers [18]. The financial transaction by using Fintech reduces the need for intermediaries like banks, cutting down fees associated with processing transactions. Instant settlements of transactions eliminate delays, reducing time-related costs for businesses and individuals. Smart contracts streamline verification and processing and reduce administrative costs. It reduces cash handling costs, such as printing, transporting, and securing cash. Fintech platforms enable instant loan disbursements and expand access to credit. Fintech solutions provide loans to underbanked populations using alternative credit. Payment infrastructure facilitates Fintech, allowing businesses and individuals to access credit from informal sources, such as friends and relatives living far away. Open Fintech platforms allow borrowers to easily compare and switch lenders, improving mobility. Fintech can enhance financial inclusion, enhancing resilience among households, individuals, and companies by providing insurance, savings, credit, money transfers, and digital distribution channels [14]. Financial inclusion can mitigate climate-related challenges, despite its negative impact [19]. The Fourth Industrial Revolution's advancements enable financial companies to offer affordable, inclusive financial solutions through Fintech, thereby enhancing environmental accessibility and affordability. This approach encourages the adoption of environmentally friendly technologies to mitigate the impacts of climate change [20]. This study points out that researchers and decision-makers should focus more on understanding the factors influencing farmers' adoption of CSATs with the help of Fintech, thereby increasing the capacity for an effective financial revolution that changes the agro-economic conditions of our country. The conceptual framework (Figure 1) of Fintech and CSA technology is based on prior research [21, 22, 23, 24, 25, 26], among others, which provides background information on the use of financial technology and the adoption of climate-smart technology in the agricultural sector.

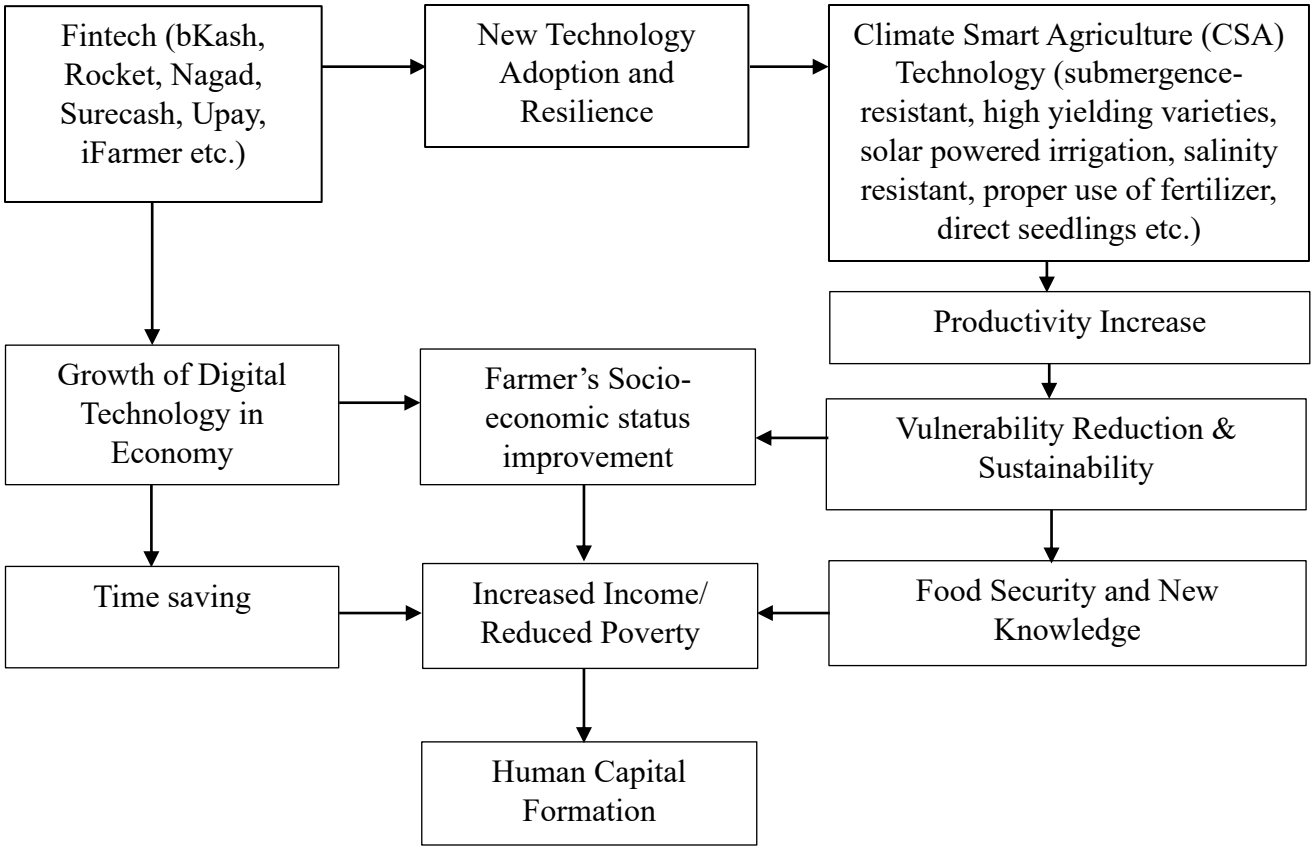


Figure 1: Pathway of Fintech and Climate Smart Agriculture Technology Adoption for Increasing Productivity

This study is situated within the Sustainable Development Goals framework, particularly SDG 2 (Zero Hunger), SDG 9 (Industry, Innovation and Infrastructure), and SDG 13 (Climate Action), where improving agricultural productivity, strengthening rural financial systems, and promoting climate-resilient farming are increasingly interlinked policy priorities. The dearth of studies analyzing the influence of Fintech on Climate Smart technology adoption and agricultural productivity in Bangladesh constitutes a gap in the study. While several studies have examined the effects of financial inclusion in developing nations, none have explicitly focused on Bangladesh's agricultural sector. Although current studies have examined financial inclusion and its broader effects, there is a noticeable gap in the literature on the influence of Fintech on the adoption of climate-smart agricultural technologies in Bangladesh's agricultural sector. Additionally, there is a need for detailed insights into how Fintech can enhance financial inclusion in agriculture, thereby promoting CSAT adoption. By addressing these gaps, the proposed study could yield significant

insights into how Fintech could transform agriculture in Bangladesh, particularly in the cultivation of rice and maize, while also facilitating the shift towards climate-smart farming practices. Understanding the link between Fintech adoption, financial inclusion, and the influence on farmers' adoption of Climate-Smart Agriculture Technologies (CSATs) is essential for addressing the concerns of Bangladesh, a climate-vulnerable nation. To increase agricultural production, resilience, and economic stability, it is necessary to investigate the potential benefits of integrating Fintech with CSA technology. This study aims to examine how fintech adoption influences the adoption of climate-smart agricultural technologies and agricultural productivity in rice and maize farming, with particular relevance to achieving SDGs 2, 9, and 13. This study can provide policymakers, scientists, and other stakeholders with vital information to make decisions aligned with institutional and governmental objectives. This study intends to determine, for the first time in Bangladesh, the impact of Fintech on the productivity of rice and maize production and on the adoption of climate-smart agricultural technologies.

Literature Review

Financial technology (FinTech) has undergone a rapid transformation in the distribution of financial services, particularly in rural areas and the agricultural sector. FinTech facilitates digital payments, mobile banking, microfinance, and credit access, which are essential for smallholder farmers who have traditionally faced challenges in accessing financial services [27]. In response to climate change, Climate-Smart Agriculture (CSA) has emerged as a strategy to increase productivity and resilience and reduce greenhouse gas emissions [28]. Despite significant advancements, the adoption of CSA technology remains limited due to financial constraints, risk perceptions, and a lack of knowledge [29]. Several scholars highlight financial barriers as a key obstacle to CSA adoption, with smallholder farmers often unable to access formal credit due to insufficient collateral, high transaction costs, and limited financial literacy [30, 31]. Arslan et al. [29] found that yields increased considerably under CSA practices in Zambia due to access to fertilizers and improved seeds. However, financial constraints hindered the widespread adoption of these practices. These studies highlight the need for FinTech-driven financial inclusion strategies to support CSA adoption.

FinTech solutions, such as mobile money and digital banking, have bridged financial gaps in rural

economies by providing low-cost, easily accessible financial services [27, 32]. Mobile money services, for instance, have reduced transaction costs and improved financial accessibility, enabling smallholders to invest in CSA technologies [32]. A study by Cai et al. [27] found that FinTech adoption significantly increased household income, employment, and non-agricultural opportunities in rural China, potentially indirectly facilitating CSA investments. However, challenges remain, including limited digital literacy and high mobile money transaction fees [33]. Research shows that policy interventions and financial education programs are necessary to mitigate these barriers and foster broader integration of FinTech in agriculture [30].

Digital lending and microfinance, as part of FinTech, have gained attention as effective means for increasing financial inclusion for farmers. Mobile microloans, peer-to-peer lending, and blockchain-based financing have been widely adopted in sub-Saharan Africa and South Asia, improving credit access for smallholder farmers [30, 34]. In Bangladesh, mobile financial services have enhanced access to credit, although challenges such as regulatory constraints and limited infrastructure persist [33]. Arslan et al. [29] say that timely access to credit is what makes CSA technologies work. Digital credit solutions can speed up loan processing, lower interest rates, and improve the accuracy of credit scoring, which makes smallholders' investments in CSA more feasible [27].

For successful FinTech adoption in CSA, strong policy support, infrastructure investment, and farmer capacity-building are essential. Countries like China have successfully integrated FinTech into agricultural development by expanding mobile banking and digital literacy programs [27]. However, in Bangladesh, infrastructural gaps, weak FinTech regulations, and inconsistent internet access present significant barriers [33].

While much research exists on FinTech adoption and CSA independently, there is limited exploration of their intersection, particularly in South Asia. Existing literature primarily addresses financial barriers and digital inclusion but lacks empirical studies on FinTech-driven CSA adoption models in Bangladesh [35, 30]. Recent studies have examined financial inclusion and climate-smart agriculture separately but have given limited attention to their intersection. From a sustainable development perspective, this gap is critical because fintech-driven financial access can serve as an enabling mechanism that links SDG 9 (financial innovation) with SDG 2 (agricultural productivity)

and SDG 13 (climate resilience) by improving the adoption of climate-smart agricultural technologies. This study contributes by examining the impact of FinTech adoption on CSA adoption among rice and maize farmers in Bangladesh, identifying key factors driving FinTech-based CSA adoption, and providing policy recommendations to enhance financial inclusion in climate-resilient agriculture. By leveraging FinTech, Bangladesh can accelerate CSA adoption, improve rural financial inclusion, and enhance agricultural sustainability.

2. Methodology

Study Area

The study was done in Kaliganj and Kaliakair Upazilas of Gazipur district, Bangladesh. Gazipur is almost the geographical center of Bangladesh, next to the rapidly expanding capital city, Dhaka [36]. The selected Gazipur district includes important infrastructure, such as the Bangladesh Agricultural Research Institute (BARI) and the Bangladesh Rice Research Institute (BRRI) [37]. Gazipur is near the city of Dhaka, and the extent of use of Information and communication technology (ICT), such as the internet, television, radio, computers, and mobile phones, among the people is highly appreciable [38]. Gazipur district offers easy access to the researcher, and the level to which people use social media such as Facebook, YouTube, Messenger, WhatsApp, etc., is noticeable [39]. Most of the agricultural extension workers in the Gazipur region had low to medium levels of expertise; however, the adoption of new technologies and understanding of ICT use are of tremendous importance for agricultural development, as they may substantially improve extension activities [40]. There was enough scope to expand extension relationships in the research zones, leading to the conclusion that more farmers need to be involved in agricultural extension in the Gazipur district [37]. Our study area, the Gazipur district, is ideal for rice farming, as is characteristic of the mid-altitude region, and over the eight years, the rice area increased from 30% to 37% [41]. In the Gazipur district, 65% of farmers adopted maize farming to a medium-to-high degree [42]. Gazipur has both access to digital financial services and rural agricultural communities. The availability of Fintech platforms such as bKash and Nagad, as well as mobile banking services, makes it easier to study how financial technology supports farmers in adopting climate-smart farming practices.

Study Type and Study Population

The study was a cross-sectional survey conducted with a structured questionnaire to achieve its goal.

Farmers of the Kaliganj and Kaliakair Upazilas of Gazipur district (Figure 2) were the study population.

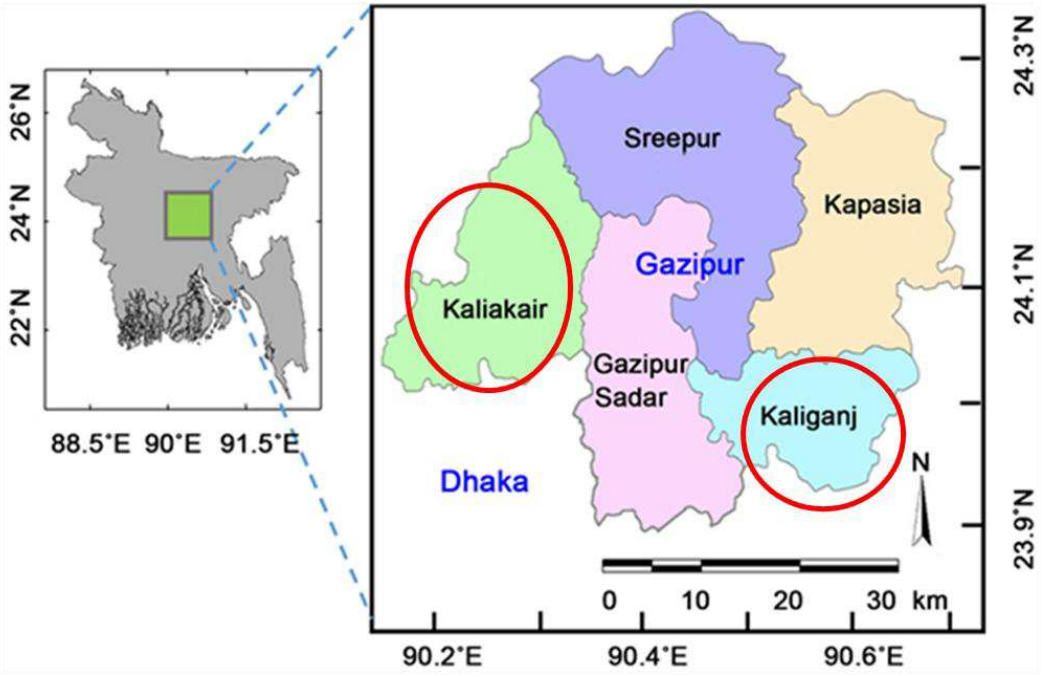


Figure 2: Sample collection based on two Upazillas in Gazipur District, Source: [43]

Bangladesh is an agro-based developing country [44]. The agricultural sector is the major driver of Bangladesh's economy and its backbone [45]. In addition to the fact that much of Bangladesh is flat and the soil is very fertile, another important fact is that the people of Bangladesh have an innate talent for farming, which is one of the key reasons they all share an interest in it [46, 47]. 40.6% of the labor force is employed in this sector [48]. The agriculture sector accounts for 47.23% of agricultural output and is the largest contributor to GDP [48]. Rice and maize were chosen for our study because of their essential contributions to global food security and economic stability, and their susceptibility to climate change. The livelihoods of millions of smallholder farmers in Bangladesh depend entirely on maize and rice. Rice and maize research play an essential role in helping Bangladesh address several agricultural challenges and increase output. In FY 2023-24, farmers harvested 40.6 million tons of rice, the highest in six years, up 4.1 percent year-on-year, and maize production reached 4.87 million tons [49]. Rice cultivation dominates Bangladesh's agriculture, accounting for 78% of the planted area and making it the country's staple food [50]. Numerous studies [12, 50, 51, 52] have investigated various aspects of rice production in Bangladesh, including production, sustainability, and farmers' socioeconomic circumstances.

Nevertheless, there exists a significant disparity in the impact of Fintech on the adoption of CSA technology in rice cultivation. In Bangladesh, maize ranks second in terms of seasonal grain output, and its popularity among farmers is growing [53]. Maize will significantly contribute, alongside other grains, to meeting the future demands of a growing population [42, 54, 55]. Still, research on the impact of Fintech on CSA technology adoption in maize cultivation in Bangladesh is hardly accessible. To ensure food security for the nation's expanding population, develop climate-resilient cultivars, and increase yields, it is important to invest in research to sustain growth in these crops.

Sampling Design and Sample Size

A multistage sampling procedure was followed in this study. Firstly, the Gazipur district was deliberately selected. Secondly,Kaliganj and Kaliakair Upazilas were selected by using the simple random sampling method. Then, three villages were randomly selected from each Upazila. Thus, six villages were chosen in all. Throughout the 2022 harvestseasons, face-to-face interviews were conducted with 240 rice- and maize-farming households, 120 from each crop, in the Kaliganj and Kaliakair Upazilas of the Gazipur district. The sample size was 240 due to budget constraints. Empirical studies mainly use quantitative methods, often with surveys. Sample sizes range from 80 to 410, and analyses include regression [56] and Partial Least Squares models [57]. Another study in Gujarat, India, involved 240 farmers to examine the adoption of climate-smart agriculture technologies [22], while 202 households were selected for a similar study in Misha district, southern Ethiopia [58]**.** Respondents were selected by using a simple random sampling method. Both qualitative and quantitative data were acquired via a questionnaire. The measure showed strong validity (Cronbach's $\alpha = 0.701$). At every stage of the respondent selection procedure, the study's objectives were prioritized.

Preparation of the Questionnaire and Collection of Data

During the questionnaire design process, particular care was taken to ensure that the wording of the questions was easy for respondents to understand. The final survey questionnaire was designed based on the findings of the pilot study. Data was carefully edited and examined after collection.

Outcome Variables

The main outcome variable of interest was the adoption of climate-smart agriculture technology. This was determined by asking farmers who had adopted CSAT, 'Do you use CSAT for rice and maize cultivation?' If a farmer indicated that they used any CSAT technology, they were classified

as a ‘CSAT Adopter’; otherwise, they were considered a ‘CSAT Non-Adopter.’ Thus, the CSAT outcome was coded as a dichotomous variable to measure CSAT adoption as follows: 1 if the farmer adopted CSAT for rice and maize production; 0 otherwise. In addition, yield was used as a response variable for productivity analysis.

Independent Variables

Several variables were considered as independent variables in this study, including age (in years), education (in years), farming experience (in years), family size, number of mobile phones, remittance, and Fintech usage. All these variables were continuous, except for gender and Fintech adoption. Gender was categorized as either male or female. According to earlier research, gender and age [59, 60, 61] have a significant impact on significant outcomes. Education, Family size, and experience in farming have been widely recognized as important independent variables [26, 59, 60]. The role of remittances [62, 63] and the number of mobile phones [63, 64] have also been explored in prior research work. The socioeconomic and behavioral outcomes are significantly influenced by these independent variables, which are demonstrated by the existing literature. Rocket, Nagad, SureCash, Upay, and iFarmer are among the top six preferred Fintech technologies [65, 66]. If a respondent adopted at least one of these technologies, they were classified as ‘Yes’ for Fintech adoption; otherwise, they were classified as ‘No. Fertilizer, labor, other inputs, and agricultural members were also used as predictors.

Statistical Analysis

For data analysis, descriptive and advanced statistical methods were utilized.

Descriptive Statistics

Descriptive analyses included calculations of frequency distribution, percentage, mean, and tabular statistics for reporting socioeconomic characteristics, age, education, farming experience, family size, member involvement in agriculture, farm size, annual family income,number of mobile phones, number of smart phones, and number of manual phones of respondents.

Statistical Analysis

Statistical models, such as the Logit and Cobb-Douglas models, were used to address the study's aims.

Logistic regression

Our response variable, adoption of CSAT, is a binary outcome, so a binary logistic regression model was applied [67, 68, 69]. A logistic model was applied to empirical data to assess the respondents' adoption of CSAT through Fintech services. Previous studies on the effect of climate-smart agriculture on household food security in South Africa [70] and the determinants of CSA practices and adoption status in Siyadebrina Wayu District [71] also used a binary logistic model. The logit model was used to identify the socio-economic factors influencing the adoption of climate-smart agricultural techniques and crop productivity among smallholder farmer households [12, 72], as well as farmers' adoption of adaptive strategies [73]. In a previous study in Malawi, the researcher used a conditional logit model to analyze household decisions on CSA options for maize production during extreme weather events [74]. Multinomial probit (MNP) and conditional logit (CL) models enable the analysis of correlations across various CSA practices [75].

$$\text{In}\,[P(Y=1)/(1-P(Y=1))] = \beta_0+\beta_1X_1+ \beta_2X_2+ \beta_3X_3+ \beta_4X_4+ \beta_5X_5+ \beta_6X_6+ \beta_7X_7 + \beta_8X_8 + U_i$$

Where, Y= adoption of CSAT (If adopted Y = 1, not adopted Y = 0)

X_1 = Gender

X_2 = Age

X_3 = Education

X_4 = Family size

X_5 = Experience in farming

X_6 = Remittance

X_7 = Number of mobile phones

$X_8 = D_{Fintech}$

U_i= Disturbance term

β_1 to β_8 are coefficients for each explanatory variable. Coefficients ($\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8$) and intercept ($\beta_0$) were calculated using the approach of maximum likelihood. SPSS was used for data analysis.

Propensity Score Matching (PSM) is frequently used to assess the impact of Fintech and CSA technologies on crop yields in future studies [76, 77]. Maximum likelihood estimates for endogenous switching regression [78] and multinomial endogenous treatment effect (METE) [21]

are also applicable to analyzing potential factors influencing the CSAT adoption decision.

Instrumental Variable Probit (IV Probit) Model

To address endogeneity bias, this study employs the Instrumental Variable Probit (IV Probit) Model**,** with data analysis conducted using the IV Probit command in Stata [79]. The IV Probit Model is specifically designed for binary dependent variables and is appropriate when the model contains endogenous regressors [80, 81]. It effectively addresses endogeneity concerns by correcting for the correlation between the endogenous regressor and the error term, ensuring consistent estimation [82].

Endogeneity may arise from unobserved factors influencing CSATs' adoption. To account for this, the IV Probit Model is used, as it is well-suited for analyzing adoption decisions in the presence of endogenous regressors [59, 61]. In this study, the adoption of mobile phones, as an endogenous regressor, is influenced by factors such as age, education, family size, farming experience, $D_{Fintech}$, Number of mobile phones (NMPs), and remittances. To address potential reverse causality between mobile phone adoption and CSAT adoption, remittance is used as an instrumental variable in the first stage. This approach is supported by previous studies demonstrating the relevance of remittance as an instrument in agricultural technology adoption [26, 83]. By leveraging the IV Probit Model, this study provides robust estimates of the relationships between Fintech, mobile phone adoption, and CSAT adoption.

The IV Probit Model consists of two steps:

First Step: In this stage, the endogenous variable, Number of Mobile Phones, is predicted to use remittance as an instrument, along with other exogenous variables such as age, education, family size, and farming experience. The instrumental variable (remittance) is assumed to influence mobile phone adoption but not to directly affect CSAT adoption, a critical assumption for the validity of this model.

$$\text{NMPs} = \gamma_0 + \gamma_1 \text{Age} + \gamma_2 \text{Education} + \gamma_3 \text{Family Size} + \gamma_4 \text{Experience in Farming} + \gamma_5 \text{Remittance} + \gamma_6 D_{Fintech} + \epsilon_2$$

Second Step: The predicted values of the number of Mobile Phones from the first stage are used as an independent variable in the second stage to estimate the likelihood of adopting CSATs. The outcome variable in this stage is binary, indicating whether a farmer has adopted CSATs.

$$CSAT^{*}=\beta_0+\beta_1 Age+\beta_2 Education+\beta_3 Family\ Size+\beta_4 Experience\ in\ Farming+\beta_5 NMPs\hat{}+\beta_6 D_{Fintech}+\epsilon_1$$

$$CSAT=\begin{cases}1, & \text{if } CSAT^{*}>0\\ 0, & \text{otherwise}\end{cases}$$

Where CSATs is a binary variable, take the value 1 if the farmer adopts CSATs and 0 if they do not. The adoption of CSAT is then determined by whether the latent variable CSAT^* is greater than zero.

Diagnostic Tests

The Durbin-Wu-Hausman Chi-squared test assesses endogeneity in mobile phone adoption [83], while the F-statistic from the first-stage regression verifies remittance as a relevant instrument, ensuring a strong correlation with the endogenous regressor [26].

Cobb-Douglas Production Function

The Cobb-Douglas model is well-suited to agricultural contexts because it provides easily interpretable elasticities and captures nonlinear relationships between inputs and outputs. It accurately captures the relationship between input and output in many practical scenarios. The model uses a log-linear form, which is a common way to estimate Cobb-Douglas functions. This transformation helps to linearize the relationship between variables and make coefficient interpretation easier. Taking logarithms makes the model's parameters linear, which simplifies the Ordinary Least Squares (OLS) estimate. This aligns with the economic principle that adding more of one input while holding others constant leads to smaller increases in output. The model allows for the assessment of how each input uniquely affects yield, while the logarithmic transformation addresses heteroscedasticity. The exponent coefficient can be interpreted as the output elasticity of an input, i.e., the percentage change in yield given a 1% change in that input. The basic form can be extended to include more factors of production or varying elasticities, making it adaptable to different economic contexts. This makes the interpretation straightforward and economically meaningful. The log-linear form efficiently models multiplicative relationships, which are common in agriculture, where inputs interact to affect output. It fits empirical data well, especially

for large economies, and is clearly interpretable in terms of parameters as output elasticities. The Cobb-Douglas production function has been utilized in various studies to assess the impact of technological factors on production, including in the context of climate-smart technologies. For instance, a study focusing on smallholder maize producers in South Africa applied a stochastic production frontier framework alongside the Cobb-Douglas function to evaluate the influence of modern agricultural technologies on maize yields [84]. Similarly, research on rice production in Japan employed a Cobb-Douglas production function and panel data analysis to examine the relationship between productive factors and output and to assess the impact of climate change on rice yields [85]. A Cobb-Douglas regression model was used to estimate the production function of rice and maize. It was used to determine the effects on rice and maize production. The advantage of using the Cobb-Douglas production function is its close alignment with economic theory and its ease of computing the partial elasticity of output with respect to inputs and returns to scale. To determine the contribution of the most important variables in the production process, the following type of Cobb-Douglas production function was used in the study.

$$Y= aX_1^{b1} X_2^{b2} X_3^{b3} X_4^{b4} X_5^{b5} X_6^{b6} X_7^{b7} X_8^{b8} X_9^{b9} e^{ui}$$

The Cobb-Douglas production function was transformed into the following logarithmic form so that it could be solved by the ordinary least squares (OLS) method.

$$\ln Y = \ln a + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \beta_4 \ln X_4 + \beta_5 \ln X_5 + \beta_6 \ln X_6 + \beta_7 \ln X_7 + \beta_8 \ln X_8 + \beta_9 \ln X_9 + U_i$$

Where, Y= Gross income from year-round rice/maize (Tk./ha);
Y= Return per hectare (Tk. /ha)
a= Intercept of the function
X_1= Fertilizer
X_2= Labor
X_3= Age
X_4= Education
X_5 = Family size
X_6 = Member involved in agriculture
X_7 = Farm size
X_8 = Number of mobile phones (NMPs)

X_9 = Remittance

$\beta_1, \beta_2 . . ….. \beta_9$ = Coefficients of the respective input to be estimated.

Like any economic model, the Cobb-Douglas production function has its limitations. Critics argue that it oversimplifies real-world complexities, ignoring factors like technological change and diminishing returns. Critics argue that these assumptions and omissions can lead to inaccurate predictions and policy recommendations in certain situations. The function assumes that all inputs of the same type are identical and interchangeable, which is unrealistic; for instance, two units of labor are not identical. Other functions, such as the CES, VES, and trans-log production function, have sought to address some of these shortcomings.

3. Results

Descriptive Statistics of Variables for Rice and Maize farmers

Table 1 displays descriptive data on the study. It provides the counts of respondents, minimum, maximum, mean, standard deviation, and range for the dependent variables and covariates among riceand maize farmers. In this test, the average age and farming experience are 50.15±11.138 years and 28.617±12.359 years, respectively, for the rice farmers, and 47.683±10.689 years and 24.15±11.071 years, respectively, for the maize farmers. The average family size for the rice and maize farmersis 3.983±1.0969 and 4.767±1.588, respectively. The annual family income of the rice and maize farmers is Tk. 181.217±57.238 and Tk. 123.6±76.153, respectively. Rice farmershave an average of 2.133±0.947 mobile phones, 1.133±0.892 smartphones, and 1±0.582 manual phones, and maize farmers have an average of 2.85±1.363 mobile phones, 1.483±1.172 smartphones, and 1.35±0.755 manual phones.

Table 1. Descriptive statistics of variables for rice and maize farmers'

Variables	N	Rice Farmer				Maize Farmer			
		Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.
Age (years)	120	32	72	50.15	11.138	29	70	47.683	10.689
Education (years)	120	0	5	1.817	1.408	0	5	1.75	1.202
Experience in farming (years)	120	10	52	28.617	12.359	8	50	24.15	11.071
Family Size	120	2	7	3.983	1.097	2	10	4.767	1.588
Member involved in	120	1	3	1.45	0.565	1	3	1.483	0.624

Agriculture

Farm size (decimals)	120	15	186	89.267	48.239	10	300	91.617	73.024
Annual family income (tk.)	120	83	302	181.217	57.238	28	314	123.6	76.153
Number of mobile phones	120	0	4	2.133	0.947	0	7	2.85	1.363
Number of smartphones	120	0	4	1.133	0.892	0	5	1.483	1.172
Number of manual phones	120	0	2	1	0.582	0	4	1.35	0.755

Most preferred Fintech technologies among Rice and Maize farmers

Table 2 demonstrates the popular Fintech technologies among rice and maize farmers. bKash, Rocket, and Nagad are widely chosen among the top six favorite Fintech technologies. Clearly, 39.84% of rice farmers and 37.35% of maize farmers favor bKash. Rocketis chosen by 19.92% of rice farmers and 18.26% of maize farmers. Both rice and maize farmerschoose Upay at 4.98%, whereas rice farmers prefer iFarmer at 2.49% and maize farmers at 1.66%. Additionally, deploying these technologies can benefit agriculture. Our findings show that farmers are eager to utilize government-supported Fintech solutions such as bKash, Rocket, Nagad, Surecash, Upay, and iFarmer.

Table 2: Percentage of the most preferred Fintech technologies of Rice and Maize Producers

Fintech Services	**Rice**		**Maize**		**Overall Percentage**
	Frequency	**Percentage**	**Frequency**	**Percentage**	
bKash	48	39.84	45	37.35	38.60
Rocket	24	19.92	22	18.26	19.09
Nagad	18	14.94	21	17.43	16.19
Surecash	8	6.64	7	5.81	6.23
Upay	6	4.98	6	4.98	4.98
iFarmer	3	2.49	2	1.66	2.06

Determinants of the adoption of CSATs of Rice and Maize by using Logistic Analysis

The logistic model was used to examine the effectof Fintech on CSATs (Table 3). The descriptive parameters in this model were gender, age, education, farming experience, family size, number of mobile phones, and remittance. Here, $D_{Fintech}$ shows a 1% significance level for both rice and maize. For rice, the significance levels for education, remittances, and the number of mobile phones is 5%, while the significance levelfor family size is 10%. For maize, the significance level for education and the number of mobilephones is 5%, while the significance level for family size is 10%.

The positive coefficients for remittance, number of mobile phones, and education indicate that increases in these variables raise CSAT adoption in both crops. Farmers who used Fintech were more likely to adopt CSAT for both rice and maize than those who did not use Fintech. Among Fintech users, the odds of supporting farmers' adoption of CSAT are 2.32 times higher for rice cultivation and 1.98 times higher for wheat cultivation compared to non-users, after controlling for other predictors.

Table 3: Determinants of the adoption of CSATs of Rice and Maize by using Logistic Analysis

Variables	**Adoption of CSATs**			
	Rice		**Maize**	
	Coefficients	**t value**	**Coefficients**	**t value**
Gender	0.221	1.234	0.303	1.470
Age	-0.119	1.567	0.147	1.198
Education	0.0832**	2.001	0.0492**	2.398
Family size	-0.216*	2.890	-0.175*	2.987
Experience in farming	0.084	0.998	0.076	1.002
Remittance	0.0207**	2.289	0.0425	1.212
Number of mobile phones	0.742**	2.321	0.733**	2.488
$D_{Fintech}$	0.841***	1.703	0. 682***	1.844

***, **, and * denote significance at 1, 5, and 10%, respectively.

Diagnostic Test of IV Probit Model

The Durbin-Wu-Hausman Chi-squared test indicates endogeneity in mobile phone adoption, with statistically significant values for both rice ($p<0.05$) and maize ($p<0.05$). The first-stage regression results further support the strength of remittances as an instrumental variable, as evidenced by high F-statistic values (>10): 28.75 for rice and 25.34 for maize. These values confirm a strong, statistically significant correlation between remittances and the endogenous regressor (see Table 4).

Table 4: Results of diagnostic tests of adopting CSA practices' impact on Rice and Maize Yield

Diagnostic Test	CSAT	
	Rice	Maize
Endogeneity (Durbin–Wu–Hausman Chi-sq.) test	14.56**	12.34**
Relevance Test -F-statistic (First Stage)	28.75***	25.34***

***, **, and * denote significance at 1, 5, and 10%, respectively.

Determinants of the adoption of **CSATs of Rice and Maize by IV Probit Model**

The results from the IV Probit Model reveal that mobile phone adoption significantly influences the adoption of Climate-Smart Agriculture Technologies (CSATs) in both rice and maize farming (Table 5). Education and Fintech adoption are key drivers, with education significantly positively associated with CSAT adoption at the 1% level for both crops, and Fintech adoption positively associated with CSAT adoption at the 10% level for both rice and maize. Family size negatively impacts mobile phone adoption at the 10% level. At the same time, farming experience has a positive effect on both mobile phone adoption and CSAT adoption, though the results are not statistically significant at conventional levels. The number of mobile phones is a significant predictor of CSAT adoption at the 1% level for both rice and maize, confirming that mobile technology facilitates the uptake of climate-smart farming practices. Remittance is a strong predictor of mobile phone adoption, with a significance level of 5%. The F-statistics from the first stage confirm the instrument's relevance, ensuring the model's robustness.

Table 5: Estimated results of the IV probit model.

Variable	Rice		Maize	
	First Stage (Mobile Phone)	**Second Stage (CSAT)**	**First Stage (Mobile Phone)**	**Second Stage (CSAT)**
Main Regressors	Coef. (SE)	Coef. (SE)	Coef. (SE)	Coef. (SE)
Age	0.10 (0.09)	-0.05 (0.10)	0.15 (0.13)	-0.06 (0.10)
Education	0.25*** (0.07)	0.15* (0.08)	0.20*** (0.06)	0.14* (0.08)
Family Size	-0.12* (0.07)	-0.08 (0.06)	-0.11* (0.06)	-0.07 (0.06)

Experience in Farming	0.07* (0.10)	0.12 (0.11)	0.12 (0.09)	0.14 (0.11)
$D_{Fintech}$ (Binary)	0.65***(0.18)	0.35* (0.20)	0.60*** (0.18)	0.30* (0.18)
Number of Mobile Phones		0.75***(0.12)		0.68***(0.11)
Instrument				
Remittance	0.60** (0.28)		0.55* (0.31)	
Constant	-1.20*** (0.30)	-0.50* (0.25)	-1.25*** (0.33)	-0.48* (0.25)
Observations	240	240	240	240
Relevance Test -F-statistic (First Stage)	28.75***		25.34***	

***, **, and * denote significance at 1, 5, and 10%, respectively.

Estimated results for the coefficients of Rice and maize production by using the Cobb-Douglas

Table 6 presents the estimation findings. According to Cobb-Douglas criteria, the adjusted R-squared for rice is 0.57 while the adjusted R-squared for maize is 0.51. This essay focuses on mobile phone penetration rates. According to our predictions, the computed Cobb-Douglas coefficients of the number of mobile phones are statistically significant for both crops. This shows that the number of mobile phones has a very beneficial impact on both rice and maize production. There is no statistically significant difference in the predicted fertilizer coefficients for maize.Fertilizer's yield elasticity in the production of rice is considerably positive, which implies thatfertilizers may be able to boost rice output. Additionally, the results indicate that the estimatedlabor and other input coefficients for rice and maize are not statistically significant, suggestingthat neither labor inputs nor other inputs can significantly increase crop yield. The sample farmers also provided more labor and other inputs than was considered to be the mostadvantageous level from an economic standpoint. Regarding the characteristics of individual farmers, the coefficients for age, number of years of schooling, and involvement in agriculture are not statistically significant, indicating that these factors do not significantly affect crop productivity. However, for both rice and maize, the family-size coefficients are statistically significant and negative, indicating that production of both crops has declined. The coefficients for remittance for both rice and maize are statistically significant, indicating that remittance may boost yields of both crops.Additionally, only for rice do the computed hybrid variety dummy coefficients show statisticalsignificance and are positive. The computed Fintech dummy coefficients for rice and maize arestatistically significant, indicating that Fintech has a beneficial effect on both crops.

Therefore, according to the Cobb-Douglas specification, the quantities of mobile phones and Fintech affect the production of rice and maize.

Table 6. Estimated results for the coefficients of Rice and maize production by using Cob- Douglas: Ln (yield)

Independent variable	Rice		Maize	
	Coefficient	**t-value**	**Coefficient**	**t-value**
Ln (Fertilizer)	0.062*	1.701	0.025	1.422
Ln (Labor)	0.017	0.987	0.041	1.110
Ln (Other inputs)	.023	1.327	0.031	0.729
Ln(Age)	0.038	1.001	0.054	1.392
Ln(Education)	0.005	0.998	.002	1.243
Ln(Family size)	-0.340*	1.860	-0.456**	2.179
Ln(Member involved in agriculture)	0.014	1.221	0.021	1.198
Ln(Farm size)	0.064	1.021	0.048	1.345
Ln(Number of mobile phones)	0.1947**	5.405	0.0733**	4.781
Remittance	0.017**	2.306	0.024**	2.021
$D_{Fintech}$	0.136***	3.052	0.183***	3.110
Constant	-8.410***	4.073	6.021***	5.959
R^2	0.57		0.51	

***, **, and * denote significance at 1, 5, and 10%, respectively.

4. Discussion

This study aimed to determine the impact of Fintech on the adoption of CSA technologies, specifically whether Fintech use affected farmers' adoption of CSA technologies in rice and maize production. The study was conducted in Gazipur, with a sample size of 240, including both rice and maize farmers. Descriptive and logistic regression analyses were used to analyze the results. From the findings, it's evident that farmers' use of Fintech services has a significant and positive effect on the adoption of CSA technologies, meaning that if a farmer uses Fintech or mobile financial services, the probability of adopting CSA technologies will increase. The most preferred Fintech service among rice and maize farmers was bKash. Other factors that affect CSA technology adoption were found to be education, family size, remittance earnings, and the number of mobile phones owned by farmers. This study also analyzed the effect of Fintech on rice and

maize production. The findings demonstrate that the use of Fintech services affects rice and maize yields, indicating that such technologies increase yields of both crops. Other factors that affect rice and maize production are family size, number of mobile phones, remittances, and the use of hybrid varieties. Although fertilizer was a factor for an increase in rice yields, that wasn't the case for maize. The findings suggest that fintech functions as an enabling channel for sustainable agricultural transformation by reducing financial constraints that limit investment in climate-smart technologies. This mechanism links rural financial inclusion with productivity improvements, thereby supporting SDG 9 through digital financial infrastructure, SDG 2 through enhanced agricultural output, and SDG 13 through strengthened climate resilience in farming systems. Overall, the findings support the conclusion that the use of financial technologies positively impacts the adoption of CSA technologies in agriculture and can help increase rice and maize yields.

The existing literature further supports the view that the use of Fintech positively influences the agricultural sector through the adoption of CSA technologies. In a study of various crops, microdosing and seed priming emerged as the predominant technologies for maize among households in Mali [86]. The research conducted by Mapanje et al. [87] across 17 Sub-Saharan African countries revealed that Fintech has the potential to play a pivotal role as a "support system" in driving sustainable agriculture in the region. Furthermore, the study highlighted that these technologies can help improve the efficiency of financing for smallholder agriculture and expand the use of sustainable agricultural methods. An earlier finding shows that Fintech products and services, such as mobile banking, digital financial services, digital crop insurance, solar energy, and blockchain technology, affect agricultural finance, boosting growth, financial inclusion, and cultivation by making agriculture a more desirable career [88]. Fintech offers practicality, ease of access, comfort, and cost-effectiveness to Indonesian society, but farmers' education levels and the availability of infrastructure affect their access in urban and rural areas [89]. A study in West Africa revealed that social factors such as age, education, experiences in production systems, gender, marital status, and cooperative membership significantly influence the adoption of CSA technology [90].

For maize education and the number of mobile phones, the significance level is 5%, and for family size, it is 10% for CSA technology. However, if selection bias was not accounted for in the study, the estimate may have been overstated. The positive effects on rice productivity are consistent

with previous findings on the effects of technology [91, 92, 93], but the results are also at odds with several studies [94, 95]. We also found a positive impact of Fintech application on total value. The prevalence of mobile phones greatly increases both rice and maize productivity. In a study conducted in Tanzania [96], similar findings were observed, highlighting that farmers' adoption of mobile phones led to significant improvements, including increased maize yields, higher agricultural profits, and reduced farming expenses. Maize production increased by approximately 124 kg/acre among farmers with access to mobile money services, and their risk of going hungry decreased by nearly 25% [97]. A study conducted in India by Mittal and Mehar [98] revealed that 35% of farmers who used mobile phones for market connectivity, to obtain improved prices, and to access agricultural information reported increased crop yields. Additionally, a separate study conducted in Ghana by Issahaku et al. [99] found that farmers with access to mobile phones experienced an average maize yield increase of 261 kg/ha per production season, exceeding that of farmers without such access. Smallholder farmers have great potential to connect to agricultural value chains in their respective nations and regions through digital payment systems [100]. Furthermore, the findings suggest that the labor and other input coefficients estimated for rice and maize are not statistically significant, indicating that neither labor inputs nor other inputs have a significant impact on increasing crop yield. Moreover, the sample farmers exceeded the optimal levels of labor and other inputs from an economic perspective, suggesting that additional inputs did not yield notable benefits in crop productivity. The estimates from the empirical models indicate that labor has a significant impact on the output of rice farming households [101]. For both rice and maize, the family-size coefficients are statistically significant and negative, indicating that yields have declined. The impact of household size (HS) on output was negative, though not statistically significant. This may be attributed to larger families allocating a considerable portion of their resources to durable consumption goods and developmental activities, rather than prioritizing agricultural modernization [102]. In contrast to a previous study conducted in Tanzania by Urassa [103], the current study's findings do not provide statistical evidence of a relationship between family size and maize yield. On the other hand, the coefficients on remittances are statistically significant for both rice and maize, indicating that remittances can help increase yields of both crops. In the context of remittance products, digital connectivity enables direct linkage to farmers' savings accounts, allowing them to save funds for future use rather than making immediate cash

withdrawals [87]. Furthermore, the statistical analysis reveals that only for rice are the estimated coefficients of the hybrid variety dummy variable both statistically significant and positive. Farms that transitioned from local varieties to high-yielding varieties (HYVs) observed a significant increase in yield, with yields approximately 35% higher, and achieved a substantial profit boost of 76% from Aman rice compared to farms that did not adopt HYVs [104]. According to findings from a two-year study conducted in Nepal, both the maize hybrid Gaurab and the open-pollinated variety (OPV) Deuti demonstrate comparable performance in grain yield and yield components [105].

In the analysis, $D_{Fintech}$ exhibited significance at the 1% level for both rice and maize CSAT adoption. The statistical analysis indicates that the estimated coefficients of the Fintech dummy variable are statistically significant for both rice and maize. Given the increase in rice yield, this finding is easily understandable. Higher total value was also reported in several studies on the effects of Fintech on the adoption of CSA practice [14, 106, 107, 108]. Although our study found a positive influence of financial technologies on the adoption of CSA technologies, Okyere et al. [109] found that mobile money adoption, a financial technology, did not affect the adoption of CSA practices. They found no statistically significant relationship between them. But they pointed out that their results are policy-relevant, given the urgent need to improve financial inclusion interventions to promote sustainable agricultural practices among farm households in developing countries.

Adoption of CSATs increases farmers' climate resilience. But CSA technologies are costly, and financial constraints are an immense barrier to their adoption. Therefore, financing is crucial to adopting CSA technology. Farmers will need financial resources to access climate-smart technologies on their farms. Innovative financial technologies can improve access to finance for CSA technologies [110]. Overall, Fintech services, such as mobile financial services, can play a crucial role in helping farmers adopt climate-smart agricultural technologies. As this topic is considerably new, further research is needed to explore and identify more insights on this matter.

Limitations of our Study

The sample size of 240 was chosen based on the available funds for our study. The limitation of our study is that we concentrated only on our specific study location, without national representation. The findings may not completely reflect the national context. A nationally representative sample will provide more extensive insights, enhancing the utility of the results for

policymakers and local smallholder farmers. Future researchers should focus on the sample size and on ensuring national representation to improve the generalizability of the findings.

5. Conclusion

Every year, our agricultural production and farmers suffer from the consequences of climate change. To tackle the hardships posed by extreme weather events and weather variability, farmers need to adopt climate-smart agricultural technologies that make them and the food system climate-resilient. As CSA technologies are costly, farmers need financial resources. Financial technology services can help farmers facilitate those resources. The study concludes that fintech adoption plays a supportive role in improving the adoption of climate-smart agricultural technologies and agricultural productivity, indicating a broader contribution to sustainable agricultural transformation. These effects align with SDG 2 through food security and productivity gains, SDG 9 through strengthened digital financial inclusion, and SDG 13 through enhanced climate resilience in farming practices. This study analyzed the effect of Fintech on CSAT adoption in Bangladesh. The findings indicate that farmers' use of Fintech services such as bKash, Rocket, and Nagad significantly increases the probability of their adoption of CSATs. Farmers' education, farming experience, family size, and access to mobile phones significantly contributed to the adoption of CSATs in both rice and maize production. The results also suggest that financial technology has a positive impact on rice and maize productivity. In conclusion, Fintech services can help farmers mitigate climate-related risks by facilitating the adoption of CSA technologies. Policies should be undertaken to increase the provision of Fintech services to the farmers so they can secure climate-resilient resources for sustainable agriculture. Future research can suggest ways to integrate financial inclusion with the adoption of CSATs. Follow-up research should analyze access to Fintech and its wider implications across diverse conditions to gain a more comprehensive picture of the potential and limitations of CSATs.

References

[1] Demirguc-Kunt, A., Klapper, L., Singer, D., Ansar, S., & Hess, J. (2018). The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution. World Bank Publications.

[2] Islam, N., Mubassira, Q. N., Huda, R. B., & Fuad, A. (2021). Adoption of FinTech in Financial

and Investment Companies of Bangladesh. Available at SSRN 4938353.

[3] Feyen, E., Frost, J., Gambacorta, L., Natarajan, H., & Saal, M. (2021). Fintech and the digital transformation of financial services: implications for market structure and public policy. BIS papers.

[4] Sironi, P. (2016). FinTech innovation: from robo-advisors to goal-based investing and gamification. John Wiley & Sons.

[5] Arner, D. W., Barberis, J., & Buckley, R. P. (2015). The evolution of Fintech: A new post-crisis paradigm. Geo. J. Int'l L., 47, 1271.

[6] Dorfleitner, G., Hornuf, L., Schmitt, M., Weber, M., Dorfleitner, G., Hornuf, L., ... & Weber, M. (2017). Definition of FinTech and description of the FinTech industry. FinTech in Germany, 5-10.

[7] Mahmud, K., Joarder, M. M. A., & Muheymin-Us-Sakib, K. (2022). Adoption factors of FinTech: evidence from an emerging economy country-wide representative sample—International Journal of Financial Studies, 11(1), 9.

[8] Hasan, R. (2021). Factors affecting the adoption of Fintech in Bangladesh. International Journal of Science and Business, 5(9), 156-164.

[9] Caire, D., & Spohn, S. (2022). In Asia, We Need to Calculate Credit Scores Differently to Help Women Get Loans. Asian Development Blog.

[10] Lagna, A., & Ravishankar, M. N. (2022). Making the world a better place with fintech research. Information Systems Journal, 32(1), 61-102.

[11] Mention, A. L. (2019). The future of fintech. Research-Technology Management, 62(4), 59-63.

[12] Sarker, M. M. R., Khan, M., Parvin, M. M., Jury, F. H., & Fagun, A. N. (2022). Determinants of Adoption of Climate-Smart Agriculture Technologies in Rice Production in Bangladesh. American Journal of Environmental Protection, 11(4), 97-102.

[13] World Bank. (2017). Climate-Smart Agriculture in Bangladesh. CSA Country Profiles for Asia Series. International Center for Tropical Agriculture (CIAT); World Bank. Washington, D. C. 28 p.

[14] Mhlanga, D. (2022). The role of financial inclusion and FinTech in addressing climate-related challenges in Industry 4.0: Lessons for Sustainable Development Goals. Frontiers in Climate, 4, 949178.

[15] Koomson, I., & Danquah, M. (2021). Financial inclusion and energy poverty: Empirical evidence from Ghana: Energy Economics, 94, 105085.

[16] Omar, M. A., & Inaba, K. (2020). Does financial inclusion reduce poverty and income inequality in developing countries? A panel data analysis—Journal of economic structures, 9(1), 37.

[17] Ouechtati, I. (2020). The contribution of financial inclusion to reducing poverty and income inequality in developing countries. Asian Economic and Financial Review, 10(9), 1051.

[18] World Bank. (2024). How financial institutions can create a climate-smart future for the agricultural sector, World Bank.https://blogs.worldbank.org/en/climatechange/how-financial-institutions-can-create-a-climate-smart-future-for

[19] Liu, D., Zhang, Y., Hafeez, M., & Ullah, S. (2022). Financial inclusion and its influence on economic and environmental performance: demand and supply perspectives. Environmental Science and Pollution Research, 29(38), 58212-58221.

[20] Ullah, S., Ali, K., Shah, S. A., & Ehsan, M. (2022). Environmental concerns of financial inclusion and economic policy uncertainty in the era of globalization: evidence from low- and high-globalized OECD economies. Environmental Science and Pollution Research, 29(24), 36773-36787.

[21] Affoh, R., Zheng, H., Zhang, X., Wang, X., Dangui, K., & Zhang, L. (2024). Climate-Smart Agriculture as an Adaptation Measure to Climate Change in Togo: Determinants of Choices and Its Impact on Rural Households' Food Security. Agronomy, 14(7), 1540.

[22] Hebsale Mallappa, V. K., & Pathak, T. B. (2023). Climate-smart agriculture technologies adoption among small-scale farmers: a case study from Gujarat, India. Frontiers in Sustainable Food Systems, 7, 1202485.

[23] Akter, A., Geng, X., Mwalupaso, G. E., Lu, H., Hoque, F., Ndungu, M. K., & Abbas, Q. (2022). Income and yield effects of climate-smart agriculture (CSA) adoption in flood-prone areas of Bangladesh: Farm-level evidence: Climate Risk Management, 37, 100455.

[24] Abegunde, V. O., & Obi, A. (2022). The role and perspective of climate smart agriculture in Africa: A scientific review. Sustainability, 14(4), 2317.

[25] Khan, N. A., Shah, A. A., Tariq, M. A. U. R., Chowdhury, A., & Khanal, U. (2022). Impact of Farmers' Climate Risk Perception and Socio-Economic Attributes on Their Choice of ICT-Based Agricultural Information Services: Empirical Evidence from

Pakistan. Sustainability, 14(16), 10196.

[26] Sardar, A., Kiani, A. K., & Kuslu, Y. (2021). Does the adoption of climate-smart agriculture (CSA) practices improve farmers' crop income? Assessing the determinants and their impacts in Punjab province, Pakistan. Environment, Development and Sustainability, 23, 10119-10140.

[27] Cai, Y., Huang, Z., & Zhang, X. (2024). FinTech adoption and rural economic development: Evidence from China. Pacific-Basin Finance Journal, 83, 102264.

[28] Lipper, L., Thornton, P., Campbell, B. M., Baedeker, T., Braimoh, A., Bwalya, M., ... & Torquebiau, E. F. (2014). Climate-smart agriculture for food security. Nature Climate Change, 4(12), 1068-1072.

[29] Arslan, A., McCarthy, N., Lipper, L., Asfaw, S., Cattaneo, A., & Kokwe, M. (2015). Climate-smart agriculture? Assessing the adaptation implications in Zambia. Journal of Agricultural Economics, 66(3), 753-780.

[30] Agyekumhene, C., de Vries, J. R., van Paassen, A., Macnaghten, P., Schut, M., & Bregt, A. (2018). Digital platforms for smallholder credit access: The mediation of trust for cooperation in maize value chain financing. NJAS-Wageningen Journal of Life Sciences, 86, 77-88.

[31] Isaga, N. (2018). Access to bank credit by smallholder farmers in Tanzania: a case study. Afrika focus, 31(1), 241-256.

[32] Kikulwe, E. M., Fischer, E., & Qaim, M. (2014). Mobile money, smallholder farmers, and household welfare in Kenya. PloS one, 9(10), e109804.

[33] Hossain, I. (2023). Financial Inclusion in Bangladesh Through Mobile Financial Services: a case study on marginal agricultural peoples of Bangladesh.

[34] Hinson, R., Lensink, R., & Mueller, A. (2019). Transforming agribusiness in developing countries: SDGs and the role of FinTech. Current Opinion in Environmental Sustainability, 41, 1-9.

[35] Aggarwal, P. K., Jarvis, A., Campbell, B. M., Zougmoré, R. B., Khatri-Chhetri, A., Vermeulen, S. J., ... & Yen, B. T. (2018). The climate-smart village approach. Ecology and Society, 23(1).

[36] Khandaker, N. I. (2022). Assessing the impact of urbanization on the declining groundwater level of Gazipur District, Bangladesh.

[37] Haq, A. Z. M. (2013). The impact of agricultural extension contact on crop income in Bangladesh. Bangladesh Journal of Agricultural Research, 38(2), 321-334.

[38] Kafura, R. A., Afrad, M. S. I., Prodhan, F. A., & Chakraborty, D. B. (2016). Use of ICT as an extension tool by farmers in Gazipur district, Bangladesh. Indian research journal of extension education, 16(2), 1-5.

[39] Hasan, S., Afrad, M. S. I., Hoque, M. Z., & Saha, S. (2023). Use of social media by the farmers in the Gazipur district of Bangladesh. Annals of Bangladesh Agriculture, 27(1), 105-120.

[40] Prodhan, F. A., & Afrad, M. S. I. (2014). Knowledge and perceptions of extension workers regarding ICT utilization in agricultural extension service delivery in the Gazipur district of Bangladesh. International Journal of Agricultural Research, Innovation and Technology, 4(2), 46-52.

[41] Shapla, T., Park, J., Hongo, C., & Kuze, H. (2015). Agricultural land-cover change in Gazipur, Bangladesh, in relation to the local economy, was studied using Landsat imagery. Advances in Remote Sensing, 4(3), 214-223.

[42] Huda, M. Z., Haque, M. E., Kabir, M. S., & Akhter, R. (2006). Adoption of modern maize cultivation in Kapasia Upazilla, Gazipur District. Int. J. Sustain. Crop Prod, 1(2), 39-43.

[43] Rony, S. A., Islam, M. A., & Alam, M. Z. (2021). Small-scale farmers' perceptions and practices of coccidial management on broiler farms in Gazipur, Bangladesh—Annals of Parasitology, 67(1).

[44] Rahman, M. T. (2017). Role of agriculture in Bangladesh's economy: uncovering the problems and challenges. International Journal of Business and Management Invention, 6(7).

[45] Hossain, M. A., & Chen, S. (2022). The decoupling study of agricultural energy-driven CO2 emissions from agricultural sector development. International Journal of Environmental Science and Technology, 19(5), 4509-4524.

[46] Chowhan, S. (2021). Impact of agro-technology on the socio-economic conditions of the farming groups of Jagannathpur. International Journal of Agriculture, Environment and Biotechnology, 14(1): Pp. 97-109. https://doi.org/10.30954/0974-1712.01.2021.11

[47] Masud, M. T., & Bhowmik, S. (2018). Feasibility study of solar-powered hydroponic fodder machine in Bangladesh. In Renewable Energy in Developing Countries: Local Development and Techno-Economic Aspects (pp. 85-94). Cham: Springer International Publishing.

[48] Bangladesh Bureau of Statistics. (2022). Yearbook of agricultural statistics-2021. 33rd series, Bangladesh Bureau of Statistics (BBS). Statistics and Informatics Division (SID), Ministry of Planning. Government of the people's republic of Bangladesh. Dhaka, Bangladesh. Pp. 03-664.

[49] Bangladesh Bureau of Statistics. (2024). Statistical Yearbook of Bangladesh 2023-24. Ministry of Planning, Government of Bangladesh.

[50] Ahmed, J. U., Kashem, M. A., Abedien, M. J., Ahamed, T., Jannat, A., & Islam, M. M. (2025). Socio-ecological factors influencing boro rice yield and profitability in Wetland areas of Bangladesh: an integrated assessment. Discover Agriculture, 3(1), 1-18.

[51] Mottaleb, K. A., Mohanty, S., & Nelson, A. (2015). Factors influencing hybrid rice adoption: a case from Bangladesh. Australian Journal of Agricultural and Resource Economics, 59(2), 258-274.

[52] Sarkar, M. S. K., Hasan, M. R., Feardous, M. A., Shuhel, M. M. H., & Moniruzzaman, M. (2010). Comparative economic analysis of borrower and non-borrower Boro rice farmers in some selected sites of Mymensingh District. Bangladesh Journal of Agricultural Research, 35(1), 65-76.

[53] Hasan, N., Jone, M. J. H., Das, B., Siddique, M. N. A., Islam, Y., & Kashem, M. A. (2025). Genetic parameter analysis and evaluation of maize hybrids under the local climatic conditions of Mymensingh, Bangladesh. Heliyon, 11(1).

[54] Islam, M. R., & Hoshain, S. (2022). A brief review of the present status, problems, and prospects of maize production in Bangladesh. Research in Agriculture, Livestock and Fisheries, 9(2), 89-96.

[55] Rahman, S., Kazal, M. M. H., Begum, I. A., & Alam, M. J. (2016). Competitiveness, profitability, input demand, and output supply of maize production in Bangladesh: agriculture, 6(2), 21.

[56] Kakkavou, K., Gemtou, M., & Fountas, S. (2024). Drivers and barriers to the adoption of precision irrigation technologies in olive and cotton farming—Lessons from Messenia and Thessaly regions in Greece. Smart Agricultural Technology, 7, 100401.

[57] Langer, G., Schulze, H., & Kühl, S. (2024). From intentions to adoption: Investigating the attitudinal and emotional factors that drive IoT sensor use among dairy farmers. Smart Agricultural Technology, 7, 100404.

[58] Mossie, W. A. (2022). The Impact of Climate-Smart Agriculture Technology on Productivity: Does Row Planting Matter? Evidence from Southern Ethiopia: the Scientific World Journal, 2022(1), 3218287.

[59] Awotide, B. A., Ogunniyi, A., Olagunju, K. O., Bello, L. O., Coulibaly, A. Y., Wiredu, A. N., ... & Abdoulaye, T. (2022). Evaluating the heterogeneous impacts of the adoption of climate-smart agricultural technologies on rural households' welfare in Mali. Agriculture, 12(11), 1853.

[60] Agbenyo, W., Jiang, Y., Jia, X., Wang, J., Ntim-Amo, G., Dunya, R., ... & Twumasi, M. A. (2022). Does the adoption of climate-smart agricultural practices impact farmers' income? Evidence from Ghana—International Journal of Environmental Research and Public Health, 19(7), 3804.

[61] Abdul-Rahaman, A., & Abdulai, A. (2022). Mobile money adoption, input use, and farm output among smallholder rice farmers in Ghana. Agribusiness, 38(1), 236-255.

[62] Baafi, J. A., & Kwame Asiedu, M. (2025). The synergistic effects of remittances, savings, education, and digital financial technology on economic growth in Sub-Saharan Africa. Journal of Electronic Business & Digital Economics.

[63] Munyegera, G. K., & Matsumoto, T. (2016). Mobile money, remittances, and household welfare: Panel evidence from rural Uganda. World Development, 79, 127-137.

[64] Simione, F. F., & Muehlschlegel, T. S. (2023). Mobile Money, Perception about Cash, and Financial Inclusion: Learning from Uganda's Micro-Level Data. International Monetary Fund.

[65] Prodhan, M. M. H., Jalal, M. J. E., Alam, H., Mostofa, M. S., Khondker, B. H., & Khan, M. A. (2024). State and potential of digital financial services among farmers in Bangladesh: An in-depth study. Journal of Agriculture and Food Research, 16, 101209.

[66] Huda, S. S., Akter, S., & Safder, A. (2023). Use of technology in agricultural services in Bangladesh—Journal of Information Technology Teaching Cases, 20438869231208217.

[67] Saha, J., Sara, S. S., Ali, M. H., Razu, S. R., Kundu, S., Haq, I., ... & Talukder, A. (2024). Prevalence and factors associated with tobacco smoking in Bangladesh. Discover Public Health, 21(1), 101.

[68] Hossain, M. I., Habib, M. J., Zinia, F. A., Rahman, A., Methun, M. I. H., & Haq, I. (2023). Rural-urban disparities in nutritional status among ever-married women in Bangladesh:

A Blinder-Oaxaca decomposition approach. Plos one, 18(12), e0289880.

[69] Bogale, A., & Shimelis, A. (2009). Household-level determinants of food insecurity in rural areas of Dire Dawa, Eastern Ethiopia—African Journal of Food, Agriculture, Nutrition and Development, 9(9).

[70] Abegunde, V. O., Sibanda, M., & Obi, A. (2022). Effect of climate-smart agriculture on household food security in small-scale production systems: A micro-level analysis from South Africa. Cogent Social Sciences, 8(1), 2086343.

[71] Kifle, T., Ayal, D. Y., & Mulugeta, M. (2022). Factors influencing farmers' adoption of climate smart agriculture to respond to climate variability in Siyadebrina Wayu District, the Central Highlands of Ethiopia. Climate Services, 26, 100290.

[72] Petros, C., Feyissa, S., Sileshi, M., & Shepande, C. (2024). Factors Influencing the Adoption of Climate-Smart Agricultural Practices and Crop Productivity among Smallholder Farmers in Nyimba District, Zambia. F1000Research, 13, 815.

[73] Uddin, M. N., Bokelmann, W., & Entsminger, J. S. (2014). Factors affecting farmers' adaptation strategies to environmental degradation and climate change effects: A farm-level study in Bangladesh. Climate, 2(4), 223-241.

[74] Pangapanga-Phiri, I., & Mungatana, E. D. (2021). Adoption of climate-smart agricultural practices and their influence on the technical efficiency of maize production under extreme weather events. International Journal of Disaster Risk Reduction, 61, 102322.

[75] Kassie, M., Teklewold, H., Marenya, P., Jaleta, M., & Erenstein, O. (2015). Production risks and food security under alternative technology choices in Malawi: Application of a multinomial endogenous switching regression. Journal of Agricultural Economics, 66(3), 640-659.

[76] Andati, P., Majiwa, E., Ngigi, M., Mbeche, R., & Ateka, J. (2023). Effect of climate smart agriculture technologies on crop yields: Evidence from potato production in Kenya: Climate Risk Management, 41, 100539.

[77] Wordofa, M. G., Hassen, J. Y., Endris, G. S., Aweke, C. S., Moges, D. K., & Rorisa, D. T. (2021). Adoption of improved agricultural technology and its impact on household income: a propensity score matching estimation in eastern Ethiopia. Agriculture & Food Security, 10, 1-12.

[78] Islam, M. K., & Farjana, F. (2024). Impact of climate-smart agriculture practices on

multidimensional poverty among coastal farmers in Bangladesh. Communications Earth & Environment, 5(1), 417.

[79] Stata, S. (2021). Stata: Release 17. Statistical Software. StataCorp LP, College Station, TX.

[80] Skeels, C. L., & Taylor, L. W. (2015). Prediction in linear index models with endogenous regressors. The Stata Journal, 15(3), 627-644.

[81] Buzas, J. S., & Stefanski, L. A. (1996). Instrumental variable estimation in a probit measurement error model. Journal of Statistical Planning and Inference, 55(1), 47-62.

[82] Gitto, L., Noh, Y. H., & Andrés, A. R. (2015). An Instrumental Variable Probit (IVP) analysis on depressed mood in Korea: the impact of gender differences and other socio-economic factors. International Journal of Health Policy and Management, 4(8), 523.

[83] Tabetando, R., Matsumoto, T., & Fani, D. C. R. (2022). Mobile money, agricultural intensification, and household welfare: Panel evidence from rural Uganda. Journal of Agricultural and Applied Economics, 54(3), 515-530.

[84] Boakye, A. (2023). Estimating agriculture technologies' impact on maize yield in rural South Africa. SN Business & Economics, 3(8), 149.

[85] Li, C. (2023). Climate change impacts on rice production in Japan: A Cobb-Douglas and panel data analysis: Ecological Indicators, 147, 110008.

[86] Sissoko, P., Guindo, S. S., Togola, S., Dembélé, B. D., Grimsby, L. K., & Aune, J. B. (2023). Effect of the Adoption of Climate-Smart Agriculture Technologies on Cereal Production, Food Security, and Food Diversity in Central Mali: Agriculture, 13(6), 1196.

[87] Mapanje, O., Karuaihe, S., Machethe, C., & Amis, M. (2023). Financing sustainable agriculture in sub-Saharan Africa: a review of the role of financial technologies. Sustainability, 15(5), 4587.

[88] Sharma, A., Mohan, A., Johri, A., & Asif, M. (2024). Determinants of fintech adoption in an agrarian economy: A study of the UTAUT extension model in reference to developing economies—Journal of Open Innovation: Technology, Market, and Complexity, 10(2), 100273.

[89] Rufaidah, F., Karyani, T., Wulandari, E., & Setiawan, I. (2023). A review of the implementation of financial technology (Fintech) in the Indonesian Agricultural Sector: Issues, access, and challenges. International Journal of Financial Studies, 11(3), 108.

[90] Sanogo, K., Touré, I., Arinloye, D. D. A., Dossou-Yovo, E. R., & Bayala, J. (2023). Factors

affecting the adoption of climate-smart agriculture technologies in rice farming systems in Mali, West Africa. Smart Agricultural Technology, 5, 100283.

[91] Gao, Q., Cheng, C., Sun, G., & Li, J. (2022). The impact of digital inclusive finance on agricultural green total factor productivity: Evidence from China. Frontiers in Ecology and Evolution, 10, 905644.

[92] Ha, T. M., & Bac, H. V. (2021). Effects of climate-smart agriculture adoption on rice farmers' performance in Northeast Vietnam. Asian Journal of Agriculture and Rural Development, 11(4), 291-301.

[93] McIntosh, C., & Mansini, C. S. (2018). The use of financial technology in the agriculture sector (No. 872). ADBI working paper.

[94] Gautam, R. S., Kanoujiya, J., Bhimavarapu, V. M., & Rastogi, S. (2021). Financial technology and its impact on poverty in India. International Journal of Management and Humanities (IJMH), 6(3), 1-10.

[95] Reddy, P. M. K., & Kumar, A. R. (2020). A study on fintech in indian agricultural sector. Journal of Critical Reviews, 7(4), 605-607.

[96] Quandt, A., Salerno, J. D., Neff, J. C., Baird, T. D., Herrick, J. E., McCabe, J. T., ... & Hartter, J. (2020). Mobile phone use is associated with higher smallholder agricultural productivity in Tanzania, East Africa. PloS one, 15(8), e0237337.

[97] Kilombele, H., Feleke, S., Abdoulaye, T., Cole, S., Sekabira, H., & Manyong, V. (2023). Maize productivity and household welfare impacts of mobile money usage in Tanzania— International Journal of Financial Studies, 11(1), 27.

[98] Mittal, S., & Mehar, M. (2012). How do mobile phones contribute to the growth of small farmers? Evidence from India. Quarterly Journal of International Agriculture, 51(3), 227-244.

[99] Issahaku, H., Abu, B. M., & Nkegbe, P. K. (2018). Does the use of mobile phones by smallholder maize farmers affect productivity in Ghana?. Journal of African Business, 19(3), 302-322.

[100] Klapper, L., El-Zoghbi, M., & Hess, J. (2016). Achieving the sustainable development goals: The role of financial inclusion. Washington, DC: CGAP.

[101] Ninh, L. K. (2021). Economic role of education in agriculture: evidence from rural Vietnam. Journal of Economics and Development, 23(1), 47-58.

[102] Paltasingh, K. R., & Goyari, P. (2018). Impact of farmer education on farm productivity under varying technologies: case of paddy growers in India. Agricultural and Food Economics, 6(1), 1-19.

[103] Urassa, J. K. (2015). Factors influencing maize crop production at the household level: A case study of the Rukwa Region in the southern highlands of Tanzania. African Journal of Agricultural Research, 10(10), 1097-1106.

[104] Rahman, M. M., & Connor, J. D. (2022). The effect of high-yielding variety on rice yield, farm income, and household nutrition: evidence from rural Bangladesh. Agriculture & Food Security, 11(1), 35.

[105] Paudel, M. N. (2009). Evaluation of hybrid and OPV maize varieties for grain yield and agronomic attributes under farmers' field conditions at Dukuchhap. Nepal Agriculture Research Journal, 9, 17-20.

[106] Menkeh, M. I. (2021). The impact of fintech (financial technology) on smallholder farmers in Ghana. Global Journal of Business and Integral Security, 1(2).

[107] Luu, T. D. (2020). Factors influencing farmers' adoption of climate-smart agriculture in rice production in Vietnam's Mekong Delta. Asian Journal of Agriculture and Development, 17(1), 110-124.

[108] Tran, D., & Goto, D. (2019). Impacts of sustainability certification on farm income: Evidence from small-scale specialty green tea farmers in Vietnam. Food Policy, 83, 70-82.

[109] Okyere, C. Y., Atta-Ankomah, R., & Asante-Addo, C. (2024). Mobile money adoption, farm performance, and household welfare in Northern Ghana. In Financial Inclusion and Sustainable Rural Development (pp. 425-450). Singapore: Springer Nature Singapore.

[110] Villalba, R., Joshi, G., Daum, T., & Venus, T. E. (2024). Financing climate-smart agriculture: A case study from the Indo-Gangetic plains. Mitigation and Adaptation Strategies for Global Change, 29(5), 33.