International Journal of Agricultural Science, Research and Technology in Extension and Education Systems (IJASRT in EESs)
Available online on: http://ijasrt.iau-shoushtar.ac.ir
ISSN: 2251-7588 Print
ISSN: 2251-7596 Online
2025: 15(3): 121-142
10.71505/ijasrt.2025.1210129

Received: 22 April 2025
Reviewed: 01 July 2025
Revised: 26 July 2025
Accepted: 10 August 2025

Exploring Smallholder Farmers' Attitudes Toward Mechanized Agriculture: An Empirical Investigation from Selected Haor Areas of Bangladesh

Md. Asifur Rahman[1*], Md. Golam Farouque[2], Md. Asaduzzaman Sarker[3]

[1]Lecturer and [2,3] Professor Department of Agricultural Extension Education, Faculty of Agriculture, Bangladesh Agricultural University, Mymensingh, Bangladesh;
** Corresponding Author Email: asifur.agext@bau.edu.bd*

Abstract

Bangladesh's agricultural sector is undergoing significant transformation due to mechanization, addressing labor scarcity and high wage rates among producers. The study aimed to assess the smallholder farmers' attitudes toward mechanized agriculture and to identify the factors that could influence their attitudes. The study, conducted in 8 sub-districts from 4 districts, involved 600 smallholder farmers (3.5% of total population of 16,800) surveyed face-to-face setting using a structured questionnaire. The focus variable, smallholder farmers' attitudes toward mechanized agriculture, was examined using 16 statements (formulated using stimulus-response and reinforcement theory) with a five-point rating scale. The responses were categorized as "strongly disagree", "disagree", "no opinion", "agree", and "strongly agree" with positive statements receiving 1, 2, 3, 4, and 5 respectively, and negative statements receiving reverse scores. Several techniques were used to assess the measurement's validity and reliability, with Cronbach's alpha being the most important one. Multiple linear regression and stepwise regression was utilized to identify the influential factors and their contributions. The majority (81.60%) of the smallholder farmers had a favorable attitude toward mechanized agriculture. Organizational engagement, level of education, age, farm size, farming experience, yearly family income, and training received on agricultural machinery were identified as the significant influential variables, explaining 68.8% of the total variations. Promotional activities like need-based training with simplified training modules and more organizational engagement should be promoted by government bodies like the Department of Agricultural Extension (DAE) and NGOs such as BRAC and Caritas. Both young, energetic and experienced farmers should be motivated to utilize farm machinery more efficiently. The Ministry of Education and local non-governmental organizations (NGOs) should come forward with their adult education program that will ultimately help in improving the living standard of our smallholder farmers.

Keywords
Attitudes, Smallholder farmers, Key informant, Organizational engagement, Focus group.

1. Introduction

The demand for food automatically rises as the world's population grows (Albuquerque et al., 2020; Godfray et al., 2018; Sims et al., 2015). By 2050, experts predict that the world's population will have expanded to nine billion (Gu et al., 2021; Boretti & Rosa, 2019; Lal, 2016). To accommodate the expanding population, agrarian output must be augmented by 70% (Lanz et al., 2018; Sylvester, 2018). Hence, increasing crop production becomes crucial. Using traditional farming methods to meet people's food needs isn't working effectively right now (Mir et al., 2022; Kc et al., 2018; Carolan, 2017; Pretty, 2013). Hence, it is crucial to employ various sophisticated techniques to oversee agricultural operations, particularly to convert traditional farming into mechanized practices. Mechanization is a key component of making farming successful and competitive (Rahman et al., 2021; Van Loon et al., 2020; Sims & Kienzle, 2017; Diao et al., 2016). The significant increase in agricultural labor productivity via the use of powered equipment, tools, and implements as inputs is what characterizes mechanized agriculture (Fuad & Flora, 2019; Hossen, 2019; Amare & Endalew, 2016; Kelemu, 2015). It optimizes and reduces the workload of labor-intensive duties, compensates for shortages of personnel, enhances productivity, and potentially aids in the mitigation of climate change-related issues (Dally & Newman, 2021; Bhusal et al., 2020; Negrete, 2018).

Bangladesh is primarily an agricultural country, and farming is the most essential occupation there (Alamgir et al., 2021; Rahman et al., 2020; Van Schendel, 2020; Jannuzi & Peach, 2019; Hasan et al., 2018; Hassan & Das, 2015; Repon & Russel, 2014; Rahman & Salim, 2013). Small holdings make up over 60% of Bangladesh's total agricultural holdings. This is due to the country's high population density and the fact that almost 80% of the population resides in rural regions (Mujeri et al., 2021; Ali et al., 2020; Fuad & Flora, 2019). Here land is fragmented due to the inheritance laws (Yucer et al., 2016). Bangladesh is home to about 17.38 million farmers, constituting about 6.69% of the country's 170 million population, and around 15.27 million households are identified as smallholder farmers (BBS, 2020). In Bangladesh, agricultural machinery has been used since the early 1960s, when deep tube wells (DTW) were first used for irrigation of crops (Rahman et al., 2021; Reza et al., 2020; Rouf, 2019). In 2015, Bangladesh formally embraced the sustainable development goals (SDGs), and since then, efforts have been made to achieve these objectives (Rahman, 2021; Ashraf et al., 2019; Hossen, 2019). As the population grows, Bangladesh will have about 200 million people by 2030 (Hossen, 2019; Mondal, 2019). This means that the country needs to double its paddy production (Rahman et al., 2020). Conversely, farm-related occupations employ 43% of the workforce now but will account for just 36% in 2020 (BBS, 2020). The declining worker force in Bangladesh is a substantial obstacle to achieving nearly double the current paddy yield in the agricultural sector (Kabir et al., 2020; Kabir et al., 2020). Politicians and planners have acknowledged that addressing the needs of an expanding global population requires agricultural mechanization as a fundamental component. The government has implemented an effort to distribute 52,000 agricultural machines to farmers as part of a large-scale project known as the Agriculture Mechanization Project through Integrated Management (Goyal & Singh, 2020). This project, which was initiated in 2020, has a total value of Tk 3,020 crore (equivalent to 30.2 billion USD) (Rahman et al., 2020). The project's stated goals include a 15% reduction in post-harvest crop losses (including the major commodity rice), a 50% reduction in cultivation time, and a 20% reduction in expenditures (Parvez & Byron, 2020).

The large, bowl-shaped, low-lying wetland in the northeastern part of Bangladesh is known as haors (Islam et al., 2022; Akhter et al., 2018; Yousuf Haroon & Kibria, 2017). With an approximate land area of 1.99 million hectares (19,998 square kilometers), it accommodates 19.37 million inhabitants (Mim & Ansari, 2021; MWR, 2012). Approximately 373 haor can be found in the greater Sylhet and Mymensingh region (Shyama et al., 2022; Haque et al., 2021; Hoq et al., 2021; Nahar et al., 2018). This particular region comprises around 43% of the entire land area of the haor districts (Sultana et al., 2023; MWR, 2012; Shyama et al., 2022). Bangladesh traditionally grows rice (Oryza sativa L.) throughout three separate seasons: Boro, Aus, and Aman (Al Mamun et al., 2021; Rahman et al., 2020). But in haor areas, only Boro rice can be grown as it goes underwater during monsoon (Awal, 2022; Biswas et al., 2019; Sourav & Abdullah, 2017). Eighteen (18%) percent of our overall Boro production is derived from Boro rice in the haor area (Kabir et al., 2020; DAE, 2018; Kamruzzaman & Shaw, 2018). In the present time, wage labor is becoming increasingly scarce, particularly in the Haor region (Alamgir et al., 2021; Islam, 2018), and heavy rains and water coming down from the Meghalaya hills in India often cause early flash floods that damage rice farming in the Haor area (Kabir et al., 2020). As a result, farmers are having various problems in the timely harvesting of paddy without the damage caused by flash floods (Dey et al., 2021). Although progress in agricultural mechanization in Bangladesh is slow, recent activities are improving day by day (Diao et al., 2020; Rahman et al., 2020). To hasten agricultural mechanization, especially in haor areas, the government and all other relevant stakeholders are putting forth maximum effort (Fuad & Flora, 2019). It is expected that the mechanized agriculture in haor areas will increase farm production, reduce farming time, reduce labor demand, save crops from flash floods and ultimately improve the living standard of smallholder farmers.

Omulo et al. (2024) studied farmers' behavioral intentions toward mechanized conservation agriculture in Zambia. Gebiso et al. (2023) investigated the factors that influence farm mechanization in the central and southeast Oromia region of Ethiopia. In the Dinajpur district of Bangladesh, Hasan et al. (2020) conducted a study on rural mechanization. In their 2020 study, Van Loon et al. investigated the impact of agricultural mechanization services on subsistence farming systems in sub-Saharan Africa, South Asia, and Latin America through scaling. Ramana and Kumari (2019) conducted a study on the perception and utilization of agricultural mechanization by farmers in the Southern Zone of Andhra Pradesh. Patil and Nalawade (2019) investigated the dimensions and determinants of farm mechanization in the irrigated region of Western Maharashtra, India. Bite et al. (2013) studied farmers' knowledge regarding farm tools and machinery in the Akola district, India. Nepal and Thapa (2009) conducted an examination of the factors that influence agricultural commercialization and mechanization in Nepal. But no studies were found on the attitude of the smallholder farmers on agricultural mechanization, especially in diverse areas like the haor region in Bangladesh. Furthermore, there is a lack of literature identifying the factors that may affect smallholder farmers' attitudes toward mechanized agriculture. Existing literature often overlooks the nuanced attitudes and socio-economic factors influencing mechanization adoption among these farmers. This study addresses this critical knowledge gap by exploring smallholder farmers' attitudes toward mechanized agriculture in the Haor region, providing helpful tips to policymakers and development practitioners aiming to design context-sensitive interventions that support sustainable agricultural transformation. That's why identifying smallholder farmers' attitudes toward the promotion of mechanized agriculture is very important. The study aimed to gather insights on the following inquiries: i) What are the current attitudes of smallholder farmers concerning mechanized agriculture in haor regions? Additionally, ii) what influences smallholder farmers' attitudes on mechanized agriculture in haor regions?

Therefore, the goals of this study were to investigate smallholder farmers' attitudes toward mechanized agriculture and to identify the factors that could influence the formation of these attitudes.

attitudes.

1.1 Hypothesis of the study

Null hypothesis (H_0)

There is no significant relationship between the selected independent variables (e.g., age, education, farm size, access to technology, etc.) and smallholder farmers' attitudes toward mechanized agriculture in the haor area of Sunamganj.

Alternative hypothesis (H_1)

There is a significant relationship between the selected independent variables and smallholder farmers' attitudes toward mechanized agriculture in the haor area of Sunamganj.

1.2 Theoretical framework of the study

This research is grounded in two core behavioral theories: the Stimulus-Response (S-R) Theory and the Reinforcement Theory, which together offer details about smallholder farmers' attitudes toward mechanized agriculture. The stimulus-response theory, which has its roots in behaviorist psychology (Watson, 1913), posits that individual behavior is a direct response to external stimuli. This research indicates that exposure to agricultural mechanization, including demonstrations of machinery use, access to mechanization services, and government initiatives, elicits cognitive and emotional responses from farmers, which in turn affects their attitudes toward the adoption of these technologies. This theoretical perspective clarifies how environmental cues and informational exposure can influence behavioral tendencies among smallholder farmers.

Furthermore, the reinforcement theory, proposed by Skinner in 1953, asserts that behavior is shaped and maintained by its consequences. The positive outcomes, including improved productivity, reduced labor costs, and time efficiencies, resulting from the adoption of mechanized practices serve as motivating factors that increase the likelihood of continued use and favorable views. Conversely, negative experiences or inadequate access to machinery may lead to resistance or diminished interest. This study assesses how farmers past experiences with mechanization influence their current attitudes, employing reinforcement mechanisms as a framework for analysis.

Theories collectively establish a comprehensive framework for examining how exposure to mechanization and its perceived effects influence attitude formation among smallholder farmers in the haor regions of Sunamganj. This dual-theory approach enables a thorough investigation of behavioral dynamics in a rural agricultural context.

2. Materials and Methods

2.1 Study location

We utilized a quantitative research methodology and developed a questionnaire to gather data via face-to-face interviews with farmers. The research was carried out at eight (08) sub-districts named Dharmapasha, Tahirpur, Itna, Mithamain, Khaliajuri, Mohanganj, Gowainghat, and Companiganj across the four (04) districts of Sunamganj, Kishoreganj, Netrakona, and Sylhet. These sub-districts were selected because they represent core haor areas where farmers face acute seasonal flooding, limited time for cultivation, poor infrastructure, and geographical isolation, all of which pose severe constraints (Brammer, 2014; Ahmed et al., 2021). Furthermore, these regions are predominantly rice-growing zones where timely mechanization is crucial for harvesting before the onset of flash floods. However, constraints such as waterlogged fields, fragmented land, and lack of hour-adapted machinery make mechanization particularly difficult (Kabir et al., 2019). Conducting the study in these diverse sub-districts provided a comprehensive view of the localized attitudes across different haor conditions while ensuring representation from both moderately and severely flood-affected areas. The Upazila Agriculture Officer (UAO) and other key individuals residing in the study area provided suggestions that were taken into account during the selection process of respondents as a sample. A map of Bangladesh and four districts showing the study area are presented in Figures 2.

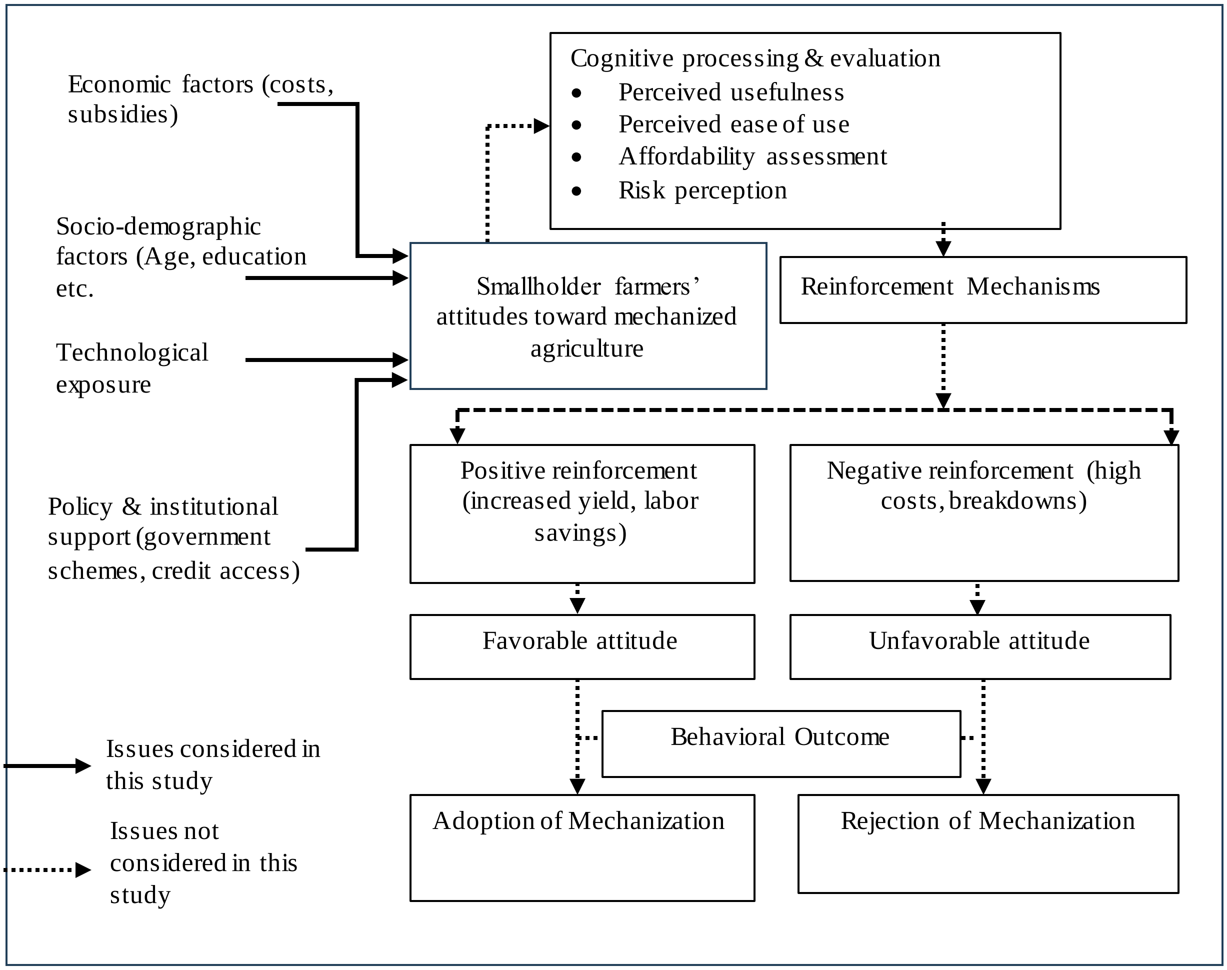

Figure 1. Theoretical framework of the study.

2.2 Population and sampling

The target population for this study comprised smallholder farmers residing in selected haor areas of Bangladesh who are engaged in crop cultivation and have experience—either directly or indirectly—in operating or attempting to operate agricultural machinery. Typically, large-scale, medium-scale, and smallholder farmers can be found in haor areas. However, medium-sized and large farmers in the haor area could afford to purchase agricultural machinery because of their increased yearly income from agriculture and other businesses (Uddin et al., 2021). So, large and medium-sized farmers are likely to have a favorable attitude towards agricultural mechanization as they operate agricultural machinery more frequently. But smallholder farmers in haor areas seldom use agricultural machinery, though they are the largest share of haor farming communities. That's why the researcher took smallholder farmers as the targeted respondents for this study.

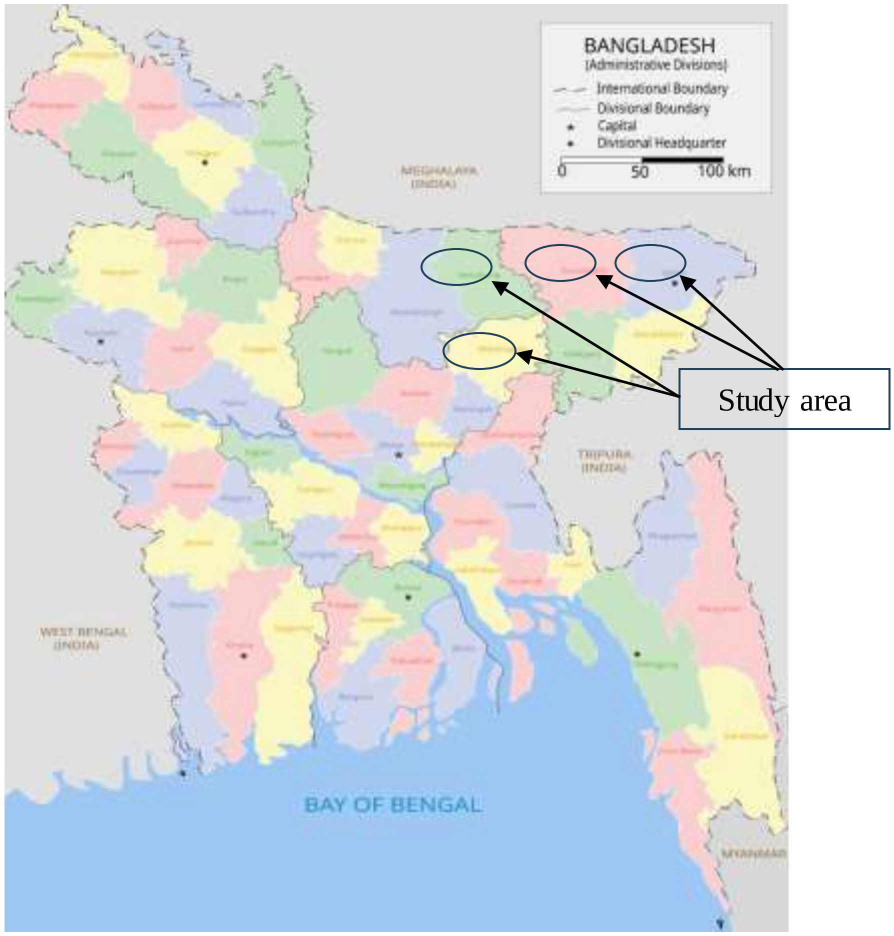

Figure 2. Map of Bangladesh indicating four districts showing the study area (Wikipedia, 2025)

Smallholder farmers in Bangladesh are those who own or manage farms with a total area of less than one hectare (1 hectare = 2.47 acres) (DAE, 1999). These farmers were selected from eight sub-districts: Dharmapasha, Tahirpur, Itna, Mithamain, Khaliajuri, Mohanganj, Gowainghat, and Companiganj, which fall under the four districts of Sunamganj, Kishoreganj, Netrakona, and Sylhet. These sub-districts were purposefully chosen due to their geographical location within the haor region and their significant dependence on seasonal agriculture, especially rice cultivation.

A multistage sampling technique was employed to ensure representation from diverse ecological and socioeconomic conditions within the haor areas. In the first stage, districts and sub-districts were selected purposively based on the intensity of haor characteristics and prevalence of mechanized farming attempts. In the second stage, villages within each sub-district were selected randomly. Finally, individual farmers were chosen using systematic random sampling from lists provided by local agricultural offices (Upazila Agriculture Officers and Sub Assistant Agriculture Officers) and community leaders.

A list of approximately 16,800 farmers who were chosen as the study's demographic was provided by an official from the Department of Agriculture (DAE), the foremost extension organization in the agricultural sector. A proportionate representation was guaranteed by selecting 75 farmers from each sub-district, resulting in a total sample of 600 farmers (approximately 3.5% of the total population) for the study. This sample size was deemed sufficient to accomplish the study's objectives, enabling the development of meaningful statistical analyses and the generalization of findings within the study areas. The inclusion criteria were centered on farmers who had either attempted to use or are presently using machinery, such as power tillers, reapers, or threshers, in their farming operations. The data collection occurred in a face-to-face environment, utilizing a structured interview schedule, spanning from March 5th to August 15th, 2023. The sample size was determined by taking into account the intended level of quality, time constraints, and the research budget (Vasileiou et al., 2018).

2.3 Research instruments

A structured interview schedule was created by conducting key informant interviews and focus group discussions, taking into account the specific objectives of the study. A pre-test was conducted with sixty (60) farmers residing in the study area prior to finalizing the questionnaire. The information was collected through a pre-tested, semi-structured interview schedule conducted in a face-to-face environment. The questionnaire featured straightforward and unambiguous questions arranged in a coherent sequence. The interviews, each approximately one hour in duration, concentrated on the farmers' attitudes toward mechanized agriculture. The data collected from the questionnaires was systematically coded and entered into the SPSS software (version 25) for thorough analysis.

2.4 Measurement of variables

The focus variable of the study was "smallholder farmers' attitudes toward mechanized agriculture". A 5-point Likert scale was used to measure this variable. Sixteen (16) statements (8 positive and 8 negative) were given to the farmers about different aspects of mechanized agriculture that were formulated using stimulus-response and reinforcement theory. The positive and negative statements were arranged consecutively. Responding to a statement was possible in five ways: "strongly disagree," "disagree," "no opinion," "agree," and "strongly agree" (Poddera et al., 2022; Hoque, 2020; Nandwani et al., 2021; Sharmin et al., 2021; Hashanuzzaman et al., 2020; Rana et al., 2020; Ntawuruhunga et al., 2020; Oo & Usami, 2020; Al-Zahrani et al., 2019; Khushi et al., 2019; Hayran et al., 2018). For positive statements, each of these responses had scores of 1, 2, 3, 4, and 5, and scoring was reversed for the negative statements (Likert, 1932). Scores for each statement could range from 16 to 80. Based on the score, farmers' attitudes were divided into five (05) different categories: strongly unfavorable (16-32), unfavorable (33-47), no opinion (48), favorable (49-64) and strongly favorable (above 64) (Sojib et al., 2022; Farouque et al., 2018; Sohel Rana et al., 2017). The total score of an individual farmer could range from 600 to 3000.

Total Score= $(N_{sa}\times5) + (N_{a}\times4) + (N_{no}\times3) + (N_{d}\times2) + (N_{sd}\times1)$

Here,

N_{sa}= Number of farmers who opined as "strongly agree"

N_{a}= Number of farmers who opined as "agree"

N_{no}= Number of farmers who opined as "no opinion"

N_{d}= Number of farmers who opined as "disagree"

N_{sd}= Number of farmers who opined as "strongly disagree"

Moreover, the explanatory variables of the farmers were assessed utilizing suitable scales shown in Table 1.

The attitude statements were formulated utilizing the Stimulus-Response (S-R) Theory and the Reinforcement Theory. The list of sixteen (16) attitude statements was presented in Table 2.

Table 1. Methods and metrics employed to quantify socio-demographic factors.

Sl. No.	Explanatory variable	Types of indicators	Measuring unit	Response scale of item
1	Age	Individual	Year	-
2	Level of education	Individual	Schooling year	-
3	Household size	Individual	Number	-
4	Farm size	Individual	Hectare	-
5	Farming experience	Individual	Years	-
6	Yearly family income	Individual	'000' Taka	-
7	Organizational engagement	Aggregated	Scale score between 0 to 24	3=President/secretary; 2=Executive member; 1=Ordinary member; 0=No participation
8	Training received on agricultural machinery	Individual	Days	-
9	Credit received	Individual	'000' Taka	-
10	Contact with extension media	Aggregated	Scale score between 0 to 36	-
11	Practices of mechanized agriculture	Aggregated	Scale score between 0 to 33	Regularly=3; Occasionally=2; Rarely=1; Not at all=0
12	Knowledge of agriculture machinery	Aggregated	Scale score between 0 to 20	Marks assigned based on the significance of the questions

*(1 Taka= 0.008 USD).

Table 2. Identified attitude statements for the farmers in haor region

No.	Attitudes statements	Theories
	Positive statements	
1	I feel encouraged to use machines because they save time and effort in farming.	(Stimulus: time-saving → Response: positive feeling)
2	Whenever I use mechanized tools, my crop yield increases, my crop loss due to flash flood decreases, which motivates me to continue.	(Reinforcement: increased yield, decrease crop loss → Response: continued use)
3	Training and demonstrations on machines increase my confidence to adopt new technology.	(Stimulus: training → Response: increased confidence)
4	I believe mechanized agriculture makes farming more profitable in the long run.	(Stimulus: profitability → Response: positive belief)
5	I receive appreciation from other farmers when I use modern machines, which makes me feel good.	(Reinforcement: social recognition → Response: satisfaction)
6	Using machines during peak farming season helps me complete work on time, encouraging repeated use.	(Stimulus: timeliness → Response: repeated behavior)
7	I am satisfied with the performance of hired machinery services in my locality.	(Stimulus: reliable service → Response: satisfaction)
8	Government support and subsidies on machines motivate me to adopt mechanized farming.	(Reinforcement: subsidy → Response: motivation)
	Negative statements	
1	I avoid using machines because they are too expensive for small-scale farming.	(Stimulus: high cost → Response: avoidance)
2	My past experience with machinery breakdowns discourages me from using them again.	(Negative reinforcement: breakdown → Response: disuse)
3	I feel stressed when using machines due to lack of proper training.	(Stimulus: lack of training → Response: stress)
4	Using machines in the haor area is risky due to waterlogging and uneven land.	(Stimulus: environmental challenge → Response: risk aversion)
5	I don't see any noticeable benefit after using machinery, so I don't plan to invest further.	(Lack of reinforcement → Response: reduced interest)
6	Sometimes machine operators charge high fees, which discourages me from hiring them.	(Stimulus: high service charge → Response: avoidance)
7	Other farmers criticize me when machines fail to perform, which makes me hesitant to use them.	(Negative reinforcement: social disapproval → Response: reluctance)
8	I feel machines are replacing traditional farming knowledge, which I value deeply.	(Stimulus: cultural conflict → Response: resistance)

2.5 Statistical analysis of data

The data were analyzed in light of the goals of the study. By applying statistical techniques such as frequency distribution, mean, percentage, standard deviation (SD), and rank order where appropriate, the chosen explanatory and focal variables were presented. According to Hamid et al. (2020), descriptive statistics provide a summary of the traits and key performance indicators of the research participants.

Before running the analytical programmes, we run a number of assumption tests to validate the data. We ran tests like tests on nonlinearity, tests of normality of residuals, tests on the presence of unusual and influential data and tests on multicollinearity using SPSS (Osemeke et al., 2024). For the test of nonlinearity, a scatterplot is used. In the case of the normality test for residuals, the normal P-P plot test and histogram are utilized. For the test of multicollinearity, VIF and tolerance values are calculated (Oke et al., 2019). For the test of the presence of unusual and influential data, Cook's Distance is calculated. Cronbach's alpha test was also run to verify that the items reliably measure the same underlying construct (Tavakol & Dennick, 2011).

Multiple linear regression analysis was used to examine the data. The researcher employed this strategy to examine the correlation between a solitary dependent variable and a set of independent variables. Multiple regression analysis was employed to ascertain influential factors that could potentially exert substantial impacts on smallholder farmers' attitude towards mechanized agriculture in haor areas. Multiple regression analysis uses the following equation:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots\dots\dots\dots + \beta_{10} X_{10} + \beta_{11} X_{11} + \beta_{12} X_{12} + e$$

Here,
Y= Focus variable (Smallholder farmers' attitudes toward mechanized agriculture),
β=Regression coefficient,
e=Error term,
X= Explanatory variable viz.,
X_1=Age,
X_2=Level of education,
X_3=Household size,
X_4=Farm size,
X_5=Farming experience
X_6=Yearly family income,
X_7=Organizational engagement,
X_8=Training received on agriculture machinery,
X_9=Credit received,
X_{10}=Contact with extension media,
X_{11}=Practices of mechanized agriculture, and
X_{12}=Knowledge on agricultural mechanization.

To obtain insight, the individual contributions of influential variables were understood through the use of stepwise multiple regression analysis (Nazif et al., 2016).

3. Results and Discussion

3.1 Characteristics profile of the smallholder farmers

Table 3 presents the profile of smallholder farmers, including their characteristics. The majority of the farmers were middle-aged, with an average age of 47.52 years and an average educational attainment of 4.28 years at the time of survey participation, according to the data shown in Table 2. That means they barely had a primary level of education. According to Makate et al. (2018), literate farmers are comparatively more innovative than illiterate farmers. Young and middle-aged farmers might have valuable opinions on receiving agricultural machinery.

Table 3. Socio‐demographic features of farmers

Characteristics (Scoring system)	Possible (Observed) score	Categories	Respondents (n=600) Number	Percentage	Mean	SD
Age (Actual years)	Unknown (23-75)	Young (18 to 35)	130	21.7	47.52	12.202
		Middle (36-55)	215	35.8		
		Old (above 55)	255	42.5		
Level of education (Schooling years)	Unknown (0-12)	Illiterate (0)	170	28.3	4.28	3.681
		Primary (1-5)	35	5.83		
		Secondary (6-10)	235	39.2		
		Above secondary (above 10)	160	26.7		
Household size (No. of members)	Unknown 3-18	Small (2- 4)	90	15.0	6.58	2.274
		Medium (5-7)	365	60.8		
		Large (above 7)	145	24.2		
Farm size (Hectares)	Unknown 0.219-0.999	Landless (0.002-0.02 ha)	0	0	0.616	0.255
		Marginal (0.021-0.2 ha)	40	6.66		
		Small (0.21-0.99 ha)	375	62.5		
		Medium (1-3 ha)	50	8.33		
		Large (>3 ha)	35	5.83		
Farming experience (Years)	Unknown 3-58	Low (3-21)	20	3.3	28.30	13.304
		Medium (22-39)	110	18.3		
		High (above 39)	470	78.3		
Yearly annual income ('000' Taka)	Unknown 32-320	Low (32-128)	30	5.0	155.76	69.395
		Medium (128.1-224)	290	48.3		
		Large (above 224)	280	46.7		
	Unknown	No participation (0)	480	80.0	0.40	0.987

Organizational engagement (Years)	0-6	Low (1-3)	85	14.2		
		Medium (4-6)	30	5.0		
		High (above 6)	5	0.8		
Training received on agricultural machinery (Days)	Unknown 0-6	No training (0)	570	95.0	0.16	0.796
		Short duration (1 to 2 days)	15	2.5		
		Medium duration (3 to 4 days)	5	0.8		
		Long duration (above 4 days)	10	1.7		
Credit received (‘000’ Taka)	Unknown 0-70	Not received (0)	430	71.7	10.68	19.436
		Low (1-23)	85	14.2		
		Medium (23.1-46)	85	14.2		
		High (above 46)	430	71.7		
Contact with extension media (Scale score)	0-36 6-19	Low (up to 12)	535	89.2	10.51	2.123
		Medium (13-24)	65	10.8		
		High (above 24)	0	0		
Practices of mechanized agriculture (Scale score)	0-33 11-25	Low (up to 11)	15	2.5	15.52	2.311
		Medium (12-22)	580	96.7		
		High (above 22)	5	0.8		
Knowledge on agricultural mechanization (Scale score)	0-20 2-14	Poor knowledge (up to 7)	385	64.2	6.91	3.074
		Moderate knowledge (8-15)	215	35.8		
		High knowledge (above 15)	0	0		

In addition to this, the average amount of time that they had spent working on an agricultural farm was 28.30 years. The families of the respondents reported an average annual income of 155.76 thousand taka, translating to approximately 1416 USD. This figure is lower than the average annual family income of 2855 USD, as indicated by HIES in 2022. The majority of the farmers had medium-sized families, with a mean score of 6.58, surpassing the national average of 4.26 for household size (HIES, 2022). The average farm size observed in the haor area was 0.616 ha, suggesting that the majority of farmers in these regions were smallholder farmers. The value is approximately equivalent to the national average farm size, recorded at 0.60 hectares (BBS, 2018).

It is important to consider that the majority of the respondents were discovered to have low organizational involvement and a mean score of 0.40. Organizational involvement has remarkable influence in the case of the agriculture machinery adoption decision by the farmers (Zhang et al., 2020). It improves willingness, motivation, and other social factors for learning new things. When an individual interacts with an organization, he acquires new knowledge and explores creative approaches to do tasks.

Participants in the study area participated in a training program for 0.16 days. Insufficient training results in a deficiency of understanding among individuals about innovative methods, technology, and the effective utilization of resources, thereby hindering their agricultural practices. The average credit obtained a score of 10.68 thousand taka. The credit amount is relatively lower as farmers had to pay a high-interest rate while returning the loan. Paying the interest rate becomes an enormous difficulty for them in the event that production falls short of expectations.

Furthermore, it is important to highlight that the average extension contact score among the majority of farmers was 10.51. This indicates a lack of communication with extension personnel in haor regions. Consequently, farmers faced a lack of numerous essential facilities. Farmers have a better chance of learning about farming tasks and new technologies when they communicate with various extension media. Poor communication facilities were also a major cause of low extension contact in haor areas. Most respondents practiced mechanized agriculture at a medium level, achieving a mean score of 15.52. Despite the limited availability of modern agriculture machinery in haor areas, there is still a regular utilization of specific kinds of agriculture machinery through rent.

A significant number of farmers exhibited a low level of knowledge, reflected by a mean score of 6.91. This may be due to a lack of higher education, limited contact with extension media and organizational involvement, inadequate training exposure and the unavailability of credit facilities.

3.2 Smallholder farmers’ attitudes toward mechanized agriculture

Smallholder farmers’ attitudes toward mechanized agriculture were the focus variable of the study. Smallholder farmers' attitude scores ranged between 47 and 70, out of a possible range of 16 to 80. The standard deviation was 3.65 and the mean score was 56.35. Respondents were put into five groups named "strongly unfavorable" (16 to 32), "unfavorable" (33 to 47), "no opinion" (48), "favorable" (49-64) and strongly favorable" (above 64) based on their attitude score, which can be seen in Figure 3. A comparable method was employed by Sojib et al. (2022) in their investigation into the perception of environmental impacts resulting from the conversion of cropland to industrial applications. The classification technique is similarly employed by Farouque et al. (2018) and Sohel Rana et al. (2017) in their individual studies.

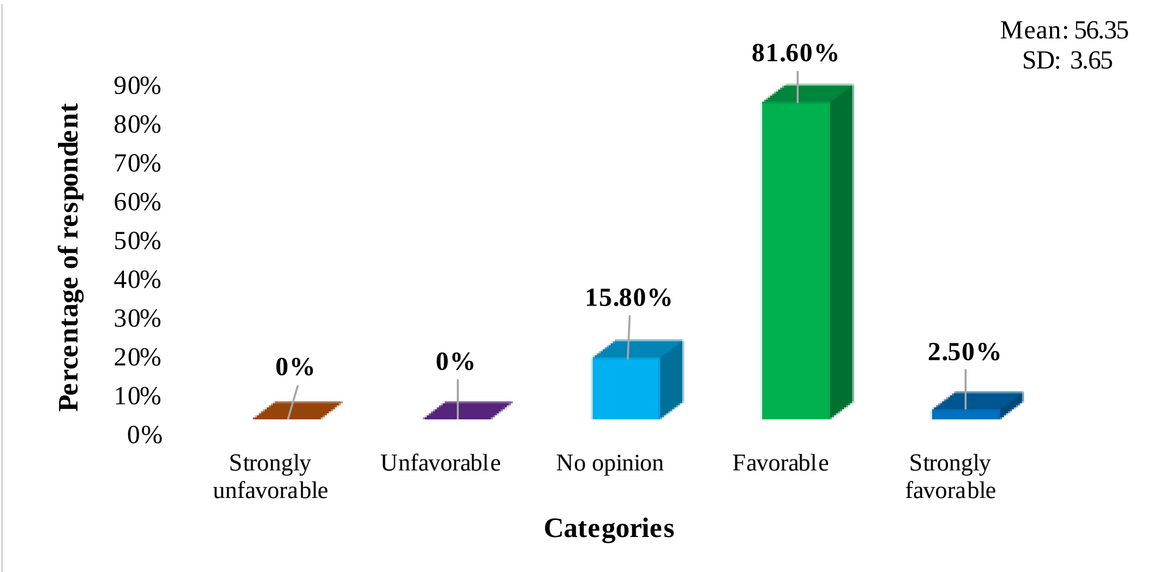

Figure 3. Distribution of smallholder farmers based on their attitudes toward mechanized agriculture

Figure 3 shows that most of the respondents who participated (81.6%) had a favorable attitude, whereas 15.8% and 2.5% had no opinion and a strongly favorable attitude toward mechanized agriculture, respectively. None of the respondents were found to have an unfavorable or strongly unfavorable attitude toward mechanized agriculture. Patil (2018) conducted a study on the factors that influence farm mechanization in the rainfed area of western Maharashtra, India. The results indicated that 73.4% of farmers had a favorable attitude, 14.58% had a highly favorable attitude, and 11.11% had a moderate attitude. None of the respondents had an unfavorable or strongly unfavorable attitude toward farm mechanization. Lambe et al. (2014) conducted a study that revealed that a significant number of farmers (66%) had a favorable attitude toward combine harvesters, with 18% expressing an extremely favorable opinion and 16% expressing a less favorable opinion. This finding is consistent with our own.

The reasons behind the favorable attitude might be the relative advantages, like reduced labor demand, quick and on-time harvesting of crops, harvesting before the damage caused by flash floods, saving in seed, increase in cropping intensity and easy availability of machinery, etc. (Fuad & Flora, 2019) of agricultural machinery over traditional tools.

However, some factors, like higher cost of operation and ongoing maintenance, low capacity for repair, lack of transparency in machinery distribution, and single cropping patterns, which made the machinery idle during the off-season, were the leading causes of only favorable attitude formation among smallholder farmers. These reasons were the significant drawback towards forming a strongly favorable attitude.

Some farmers expressed a "no opinion" attitude toward agricultural machinery because they were confused about its relative advantages. They reported that they were getting some benefits due to the use of agricultural machinery. However, they also faced several problems, such as grain shattering, high operational costs, and parts shortages during the peak season. For those reasons, farmers were confused about agricultural mechanization and provided their opinion as neutral. Table 4 displays the total scores obtained for each statement, providing insight into the respondents' attitudes and their extent.

Table 4. Extent of attitudes of smallholder farmers toward mechanized agriculture

Statements	Extent of Agreement or Disagreement					Total Score	Rank Order
	SD	D	NO	A	SA		
Positive statements							
I feel encouraged to use machines because they save time and effort in farming.	0	15	280	220	85	2175	6
Whenever I use mechanized tools, and my crop yield increases, my crop loss due to flash flood decreases, which motivates me to continue.	0	0	0	515	85	2485	2
Training and demonstrations on machines increase my confidence to adopt new technology.	0	5	5	300	290	2675	1
I believe mechanized agriculture makes farming more profitable in the long run.	50	445	35	55	15	1340	11
I receive appreciation from other farmers when I use modern machines, which makes me feel good.	30	275	35	260	0	1725	8
Using machines during peak farming season helps me complete work on time, encouraging repeated use.	0	5	20	530	45	2415	3
I am satisfied with the performance of hired machinery services in my locality.	0	125	120	315	40	2070	7
Government support and subsidies on machines motivate me to adopt mechanized farming.	5	510	15	65	5	1355	10
Negative statements							
I avoid using machines because they are too expensive for small-scale farming.	55	475	35	30	5	2345	4
My past experience with machinery breakdowns discourages me from using them again.	5	0	5	505	85	1135	12
I feel stressed when using machines due to lack of proper training.	0	25	75	75	425	900	14
Using machines in the haor area is risky due to waterlogging and uneven land.	445	135	0	10	10	805	15
I don't see any noticeable benefit after using machinery, so I don't plan to invest further.	0	30	70	100	400	930	13
Sometimes machine operators charge high fees, which discourages me from hiring them.	60	450	65	25	0	2345	4
Other farmers criticize me when machines fail to perform, which makes me hesitant to use them.	35	400	95	65	5	2195	5
I feel machines are replacing traditional farming knowledge, which I value deeply.	0	35	360	205	0	1630	9

Note: SD = Strongly Disagree, D = Disagree, NO = No Opinion, A = Agree, SA = Strongly Agree

Table 4 shows that the statement 'Training and demonstrations on machines increase my confidence to adopt new technology' received the highest score of 2675 out of a total of 3000. This statement received the highest score, indicating that the farmers need training for operating machinery. Hands-on experience and practical knowledge play a crucial role in diminishing the uncertainty and apprehension linked to unfamiliar technologies. By engaging in training and demonstrations, farmers acquire a comprehensive understanding of machine functionality, operation, maintenance, and the advantages they can provide. This hands-on engagement fosters confidence in the technology, elevates skill proficiency, and enables farmers to make well-informed choices. This leads to an increase in their confidence, which in turn makes them more open and ready to embrace contemporary agricultural innovations. In their 2020 study, Lyngdoh and Mazhar examined the perspectives of farmers regarding agricultural machinery in East Kashi Hills, Meghalaya, revealing that training and demonstrations ranked as their most favorable aspects. This body of literature corroborates our findings.

"Whenever I use mechanized tools, my crop yield increases, and my crop loss due to flash floods decreases, which motivates me to continue" received the second highest score of 2485. This is due to the observable advantages they gain from mechanization. The ongoing enhancement in yield and the decrease in losses caused by heavy rainfall and runoff from the Meghalaya hills in India (Kabir et al., 2020) present evident, favorable results that support the choice to adopt contemporary tools. The findings provide compelling encouragement for farmers to persist in embracing mechanized practices. The relationship between tool usage and enhanced productivity fosters confidence in the technology, establishing it as a practical and beneficial option for sustained application.

"Using machines during peak farming season helps me complete work on time, encouraging repeated use" received the third highest score of 2415 out of the total score. Timely operations play a crucial role in achieving success in agriculture. In peak seasons, any delays in land preparation, sowing, or harvesting can have a substantial impact on both yield and quality. Mechanized tools enable farmers to optimize their time management, decreasing reliance on limited manual labor and lowering the likelihood of crop failure caused by timing challenges. The dependability and effectiveness of mechanization render it an essential tool, prompting farmers to consistently utilize machinery as a reliable answer to seasonal time limitations. A study conducted by Kabir et al. (2020) indicates that agricultural mechanization facilitates the timely harvesting of paddy, significantly ahead of the onset of rain, thereby minimizing crop loss from flash flooding. The literature further corroborates our second and third findings.

The statements with the lowest scores were "Using machines in the haor area is risky due to waterlogging and uneven land" (total score = 805), "I feel stressed when using machines due to lack of proper training" (total score = 900), and "I don't see any noticeable benefit after using machinery, so I don't plan to invest further" (total score = 930).

3.3 Assumption test

In the nonlinearity assumption test, the analysis exhibited no heteroscedasticity and produced a plot of standardized residuals versus predicted values. For this study, the assumption was met because it created a plot of standardized residuals on the Y-axis versus predicted values on the X-axis. The following plot indicated that the points in the scatter plot did not display any discernible pattern. Therefore, heteroscedasticity was not present.

In a normal P-P plot test for multiple linear regression, the plot should form a straight diagonal line. The following points on the P-P plot showed that it roughly formed a straight diagonal line. Thus, the normality was met.

In the histogram test, a bell shape should be created to meet the assumption demand. The following graph was made specifically for this study. The peaks illustrate the predominant values and evaluate the dispersion of the sample to comprehend the extent of data variability, resulting in a bell-shaped distribution. The bars were closely aligned with the fitted distribution line, indicating a strong fit between the data and the distribution.

A standard multicollinearity test indicates that there is an absence of correlation among the variables. Additionally, the variance inflation factor (VIF) and tolerance serve as two interconnected metrics employed to assess collinearity in multiple regression analysis. The foundation is determined by the R-squared value derived from regressing one predictor against all other predictors in the analysis. A VIF value of 1 signifies the absence of correlation between a specific predictor variable and the other predictor variables. A value ranging from 1 to 5 signifies a moderate correlation between a specific predictor variable and other predictor variables within the model; however, this level of correlation typically does not necessitate immediate attention. A value exceeding 5 suggests a potentially strong correlation between a specific predictor variable and other predictor variables within the model. The multiple linear regression analysis performed in this study revealed that the variance inflation factor (VIF) values varied between 1.117 and 3.038, all remaining below the critical threshold of 5. The results demonstrate that the multicollinearity test was met, indicating that there was no correlation among the predictor variables, thus confirming the lack of multicollinearity. The VIF and tolerance values of the multiple regression models are given in Table 5.

Table 5. The collinearity statistics of the multiple linear regression model

Predictors	Collinearity Statistics	
	Tolerance	VIF
Age	0.595	1.681
Level of education	0.536	1.864
Household size	0.878	1.139
Farm size	0.420	2.380
Farming experience	0.508	1.968
Yearly family income	0.576	1.737
Organizational engagement	0.329	3.038
Training received on agricultural machinery	0.458	2.182
Credit received	0.895	1.117
Contact with extension media	0.532	1.881
Practices of mechanized agriculture	0.565	1.769
Knowledge of agriculture machinery	0.377	2.652

In a similar manner, tolerance is utilized in applied regression analysis to evaluate the levels of multicollinearity. Tolerance measures the extent to which beta coefficients are influenced by the inclusion of other predictor variables in a model. Lower tolerance values indicate increased multicollinearity levels. The tolerance is linked to each independent variable and varies from 0 to 1. Generally, a tolerance below 0.25 indicates that multicollinearity might exist, and further investigation is required. When tolerance is lower than 0.1, there is significant multicollinearity that needs to be corrected. In the above table, it is seen that the tolerance level exceeds 0.1, which met the multicollinearity test. That means none of the predictor variables were correlated with each other, which represented that no multicollinearity was present.

In standard multiple regression, unusual and influential data are not present. In this study, the X-axis belongs to independent variables (selected characteristics of farmers) and the Y-axis belongs to dependent variables. Most of the variable's data is situated near the bottom of the X-axis. There was very little data scattered here and there. Therefore, the researcher said that unusual and influential data wasn't found. Thereby, the assumptions are met for conducting multiple linear regression analysis. The test in the presence of unusual and influential data is presented in Figure 8.

Figure 10 indicates that, except for very few observations, all of the points fall within the range of negative 3 to positive 3 on either one of the X or Y-axes. So, it's in good shape because most points are between -3 and +3. Similar observations were found considering residual descriptive statistics; the standard residual range is -2.197 to 2.289 (Figure 4), which is more or less within the range of -3 to +3. An observation with a standardized residual exceeding 3 (in absolute value) is regarded as an outlier by certain scholars (Cook, 1977).

Figure 4. Descriptive statistics of the residuals of the multiple linear regression model

Cook's distance represents the scaled change in fitted values, serving as a valuable tool for detecting outliers in the X values, which correspond to observations for predictor variables. The Cook's distance is regarded as high when it exceeds 0.5 and is deemed extreme if it surpasses 1 (Cook, 1977). The findings presented in Figure 10 show that the Cook's distance ranged from 0.000 to 0.024, which is below the threshold of 0.5, suggesting that there are no influential outliers present in the model.

The internal consistency of the scale item's attitude statement was evaluated through Cronbach's alpha. The analysis revealed that the Cronbach's alpha for the 16 statements was 0.951, exceeding the threshold of 0.9. A Cronbach's alpha value greater than 0.9 indicates excellent reliability (George and Mallery, 2003). However, removing any of the factors does not influence the elevation or enhancement of the Cronbach's alpha value from 0.951. Consequently, it can be inferred that the claims regarding internal consistency or reliability were adequate. The findings suggest that the scale developed through the previously mentioned methods demonstrated reliability.

3.4 Factors influencing the attitudes of smallholder farmers toward mechanized agriculture

3.4.1 Multiple linear regression analysis

Multiple linear regression analysis was used to investigate the data. Using this approach, the researcher looked into the relationship between a set of independent factors and a single dependent variable. To identify key factors that may have substantial impacts, multiple regression analysis was conducted. The specific contributions of each of the important factors were to be ascertained by stepwise multiple regression analysis.

The correlation coefficient merely signifies the existence of a linear association between two variables. The statement fails to quantify the impact and contribution of a specific independent variable to the dependent variable. The interaction of different characteristics exhibited by the respondents may collectively impact the attitudes of smallholder farmers.

The variables such as age (X_1), level of education (X_2), household size (X_3), farm size (X_4), farming experience (X_5), yearly family income (X_6), organizational engagement (X7), training received on agriculture machinery (X_8), credit received (X_9), contact with extension media (X_{10}), practices of mechanized agriculture (X_{11}) and knowledge on agricultural mechanization (X_{12}) were considered as the independent variables for the regression analysis. For this reason, a linear regression analysis was shown in Table 6.

The findings of the linear regression analysis are detailed in Table 6. The variables demonstrated outstanding tolerance. At $p<0.01$, the F-test statistic value for the model was 111.826, demonstrating a statistically significant result. The adjusted R-squared value of 0.689 indicates that the proposed model aligns effectively with the data, and all parameters demonstrated a statistically significant impact above zero. The results of the linear regression analysis revealed that only seven (07) of the twelve (12) independent variables exhibited statistical significance: age (X_1), level of education (X_2), farm size (X_4), farming experience (X_5), yearly family income (X_6), organizational engagement (X_7), and training received on agriculture machinery (X_8).

Table 6. An overview of the smallholder farmers' attitudes as shown by multiple linear regression analysis that explains the focus variable (n=600)

Explanatory variables	Unstandardized coefficients		Standardized coefficients	t-value	Sig.
	B	Std. Error	Beta		
(Constant)	55.881	0.802		69.672	0.000
Age (X_1)	-0.075	0.009	-0.251	-8.488	0.000*
Level of education (X_2)	0.321	0.031	0.325	10.444	0.000*
Household size (X_3)	-0.044	0.039	-0.027	-1.120	0.263
Farm size (X_4)	1.846	0.503	0.129	3.671	0.000*
Farming experience (X_5)	0.005	0.002	0.096	3.013	0.003*
Yearly family income (X_6)	0.030	0.008	0.110	3.681	0.000*
Organizational engagement (X_7)	1.540	0.146	0.417	10.512	0.000*
Training received on agriculture machinery (X_8)	0.355	0.154	0.077	2.304	0.022*
Credit received (X_9)	-0.006	0.005	-0.031	-1.283	0.200
Contact with extension media (X_{10})	0.044	0.054	0.026	0.825	0.409
Practices of mechanized agriculture (X_{11})	0.011	0.048	0.007	0.223	0.824
Knowledge on agricultural mechanization (X_{12})	0.071	0.044	0.060	1.612	0.107
n=600, R=0.834, R^2=0.696, Adjusted R^2=0.689, F-value=111.826					

* Significant if $p < 0.05$, Level of significance = 95%

According to Table 6's findings, smallholder farmers' ages significantly correlated negatively with their attitudes against the advancement of mechanized agriculture, with a value of -0.075. The regression coefficient suggests that a one-year change in the age of the respondents results in a 0.075-unit change in their attitude. That means farmers who are old-aged have a negative attitude and farmers who are young and middle-aged have a positive attitude towards mechanized agriculture in haor. Patil & Veettil (2024) conducted research among rural youth and farmers in Haryana, India, revealing that age has a significant negative effect on attitudes toward agriculture-related innovations—older rural youth exhibited less favorable attitudes.

Table 6's findings showed that smallholder farmers' attitudes towards mechanized agriculture were significantly positively correlated with their level of education, with a significant positive coefficient value of 0.322. The regression coefficient suggests that a one-unit increase or decrease in educational level corresponds to a 0.322 change in attitude. That means farmers with a high level of education have a positive attitude toward mechanized agriculture. Hasan et al. (2021) reported more or less similarly in their study regarding attitudes toward farm mechanization and educational qualifications. Gebiso et al. (2023) reported similar findings that educational background had a significant influence on determinants of farm mechanization in Ethiopia.

The regression coefficient indicates that if farming experience changes by one number (one scale score), then attitude changes by 1.846. The farm size of smallholder farmers positively influences their attitudes toward mechanized agriculture because larger plots provide greater opportunities to benefit from increased efficiency, productivity, and labor savings. As farm size increases, the limitations of manual labor become more apparent, making mechanization a more attractive and practical option. Farmers with larger holdings are also more likely to view mechanization as a worthwhile investment that can improve profitability and reduce production costs. This positive perception encourages a more favorable attitude toward adopting mechanized practices. Sanaullah & Ullah (2021) reported in their study that farmers with more farming experience significantly influenced the adoption of farm mechanization in Peshawar, Khyber Pakhtunkhwa, Pakistan.

The regression coefficient indicates that if farm size changes by one number (one scale score), then the attitude changes by 0.005. The size of the farm shows a positive and substantial correlation with smallholder farmers perceptions of mechanized agriculture, as larger farms often need increased effort and time for successful management. As agricultural scale expands, the constraints of human labor become increasingly evident, leading farmers to acknowledge the advantages of technology in enhancing efficiency, alleviating toil, and boosting production. Expansive landholdings provide greater economic rationale for investing in or adopting mechanical tools, rendering the concept more attractive and feasible for these farmers. Sanaullah & Ullah (2021), in their study, reported farmers with larger farm sizes had a significant influence on the adoption of farm mechanization in Peshawar, Khyber Pakhtunkhwa, Pakistan.

The regression coefficient indicates that if yearly annual income changes by one number (one scale score), then attitude changes by 0.030. Yearly annual income showed a positive significant correlation with smallholder farmers' attitudes towards mechanized agriculture, likely because higher income provides farmers with greater financial flexibility to invest in modern technologies. Wealthier farmers are more capable of purchasing or accessing mechanized tools and are therefore more likely to perceive them as beneficial for improving productivity and reducing labor costs. This relationship has been supported by previous research; for example, Rahman et al. (2017) found that higher household income significantly influenced the adoption of agricultural technologies in Bangladesh. Similarly, Asfaw et al. (2016) reported that family income had a positive and significant effect on Ethiopian farmers’ willingness to adopt improved agricultural practices, including mechanization. These findings suggest that income level plays a critical role in shaping farmers' attitudes and decisions regarding technological advancement in agriculture.

Table 6's results showed that smallholder farmers' attitudes toward mechanized agriculture were significantly correlated with their organizational engagement, with a significant positive coefficient value of 1.552. According to the regression coefficient, there is a 1.552-unit change in attitude for every unit change in organizational engagement. That means farmers with high organizational engagement have more positive attitudes toward mechanized agriculture. This is because their involvement in cooperatives, agricultural groups, or extension services provides them with better access to information, resources, and peer support.

The regression coefficient indicates that if training received on agricultural machinery changes one number (one scale score), then the attitude changes by 0.355. Specialized training programs significantly shape smallholder farmers’ attitudes toward mechanized agriculture. Training exposes farmers to the practical benefits of machinery—such as reduced labor demands, greater speed, and precision—and builds their confidence in safely operating and maintaining equipment. As farmers participate in demonstrations and hands-on sessions, they develop direct experience with mechanization's advantages, leading to more favorable perceptions. For instance, a study in Bangladesh by Hasan et al. (2020) found that farmers' training experiences were significantly and positively correlated with their attitudes toward farm mechanization.

5.3.2 Stepwise multiple regression analysis

A stepwise multiple regression analysis was used to determine the impact of each important variable in accounting for the diversity in the smallholder farmers' attitudes toward mechanized agriculture. The tool was used to identify the important independent variables influencing the attitudes of smallholder farmers toward mechanized agriculture. The stepwise multiple regression analysis is displayed in Table 7.

Table 7. Step-wise multiple regression analysis for the attitude of smallholder farmers toward mechanized agriculture

Model	Combination of the factors	Co-efficient of determination	Adjusted R^2	Percent of increase in adjusted R^2
1	Constant + X_7	0.504	0.504	50.4%
2	Constant + X_7 + X_2	0.627	0.625	12.1%
3	Constant + X_7 + X_2 + X_1	0.665	0.663	3.8%
4	Constant + X_7 + X_2 + X_1 + X_4	0.676	0.674	1.1%
5	Constant + X_7 + X_2 + X_1 + X_4 + X_5	0.682	0.680	0.6%
6	Constant + X_7 + X_2 + X_1 + X_4 + X_5 + X_6	0.688	0.685	0.5%
7	Constant + X_7 + X_2 + X_1 + X_4 + X_5 + X_6 + X_8	0.692	0.688	0.3%

Here, X_7 = Organizational engagement; X_2 = Level of education; X_1 = Age; X_4 = Farm size; X_5 = Farming experience; X_6 = Yearly family income; and X_8 = Training received on agriculture machinery.

The stepwise multiple regression analysis revealed that organizational engagement (X_7) expresses the focus variable by 50.4%, level of education (X_2) expresses 12.1%, age (X_1) expresses 3.8%, farm size (X_4) expresses 1.1%, farming experience (X_5) expresses 0.6%, yearly family income (X_6) expresses 0.5%, and training received on agriculture machinery (X_8) expresses 0.3% attitude towards mechanized agriculture. Sheheli et al. (2023) discovered comparable outcomes, concluding that the fish farmers' communication exposure was the primary factor that helped to explain the dependent variable, or the knowledge of fish farmers in the Gauripur sub-district of Mymensingh.

4. Conclusion and Recommendations

The overwhelming percentage of the smallholder farmers were found with a favorable attitude towards mechanized agriculture. Possible factors contributing to the favorable attitude may include the comparative benefits, such as decreased labor requirements, efficient and timely crop harvesting, avoidance of damage from sudden floods, etc. Factors such as organizational engagement, level of education, age, farm size, farming experience, yearly family income, and training received on agriculture machinery were identified as the significant influential variables. Younger farmers are more open to mechanization, while older ones prefer traditional methods, but experienced ones can overcome many challenges. Prosperous, educated farmers who actively participate in organizations and receive need-based training can empower themselves to make informed decisions and positively shape their attitudes towards mechanized farming.

Promotional activities (including the provision of incentives and the increase in the availability of agricultural equipment at the local level) need to be undertaken by the concerned authorities, especially by the Department of Agricultural Extension (DAE), to strengthen the ongoing Agricultural Mechanization Project through Integrated Management. To maintain this favorable attitude of the farmers, more such projects can be undertaken by the Ministry of Agriculture and implemented at the field level with proper supervision.

To improve organizational engagement, it is crucial to strengthen farmer cooperatives as well as establish additional community-based machinery service centers with assistance from governmental entities like the Department of Agricultural Extension (DAE) and non-governmental organizations such as BRAC and Caritas. It is advisable to enhance outreach and engagement strategies by implementing regular training sessions, conducting equipment demonstrations, and fostering collaborative farming initiatives. Enhancing organizational support networks will cultivate trust and familiarity with mechanized solutions, resulting in increased adoption rates.

The Ministry of Education and local non-governmental organizations (NGOs) should come forward with their adult education program. Simplified training modules should be developed and delivered in local dialects. These programs should focus on the practical benefits and cost-effectiveness of mechanized agriculture, making the technology accessible and understandable for farmers with varying educational backgrounds. Young and middle-aged farmers should be encouraged to take part in agriculture activities by providing proper facilities like need-based training programs, initial investments with low-interest bank loans, etc.

For farmers with small landholdings, the promotion of machinery-sharing models like Custom Hiring Centers can ensure access to mechanization without the financial burden of ownership. Addressing yearly family income, microfinance schemes, subsidies, and flexible payment plans should be made available to lower the economic barriers to mechanization. Experienced farmers can be valuable change agents; thus, participatory training and peer-learning models should be introduced to combine traditional knowledge with modern methods.

References:

1. Ahmed, N., Islam, M. A., & Haque, M. E. (2021). Constraints and prospects of agricultural mechanization in haor areas of Bangladesh. Journal of Agricultural Research and Development, 21(1), 45–54. https://doi.org/10.3390/ecologies5020017

2. Akhter, H., Mia, C., & Panna, S. A. (2018). Understanding the changes of the wetland ecosystem and its impact on the biodiversity of Tanguar haor in Sunamganj, Bangladesh. Asian Journal of Environment & Ecology, 7(4), 1–11. https://doi.org/10.9734/AJEE/2018/45229

3. Alamgir, M. S., Furuya, J., Kobayashi, S., Mostafiz, R. B., & Ahmed, M. R. (2021). Farm income, inequality, and poverty among farm families of a flood-prone area in Bangladesh: Climate change vulnerability assessment. GeoJournal, 86, 2861–2885. https://doi.org/10.1007/s10708-020-10231-2

4. Albuquerque, C. K., Polimante, S., Torre-Neto, A., & Prati, R. C. (2020, November). Water spray detection for smart irrigation systems with Mask R-CNN and UAV footage. In 2020 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor) (pp. 236-240). DOI: 10.1109/MetroAgriFor50201.2020.9277542

5. Ali, M. P., Kabir, M. M. M., Haque, S. S., Qin, X., Nasrin, S., Landis, D., & Ahmed, N. (2020). Farmer's behavior in pesticide use: Insights study from smallholder and intensive agricultural farms in Bangladesh. Science of the Total Environment, 747, 141160. https://doi.org/10.1016/j.scitotenv.2020.141160

6. Al Mamun, M. A., Nihad, S. A. I., Sarkar, M. A. R., Aziz, M. A., Qayum, M. A., Ahmed, R., & Kabir, M. S. (2021). Growth and trend analysis of area, production and yield of rice: A scenario of rice security in Bangladesh. PLOS ONE, 16(12), e0261128. https://doi.org/10.1371/journal.pone.0261128

7. Al-Zahrani, K. H., Khan, A. Q., Baig, M. B., Mubushar, M., & Herab, A. H. (2019). Perceptions of wheat farmers toward agricultural extension services for realizing sustainable biological yields. Saudi Journal of Biological Sciences, 26(7), 1503–1508. https://doi.org/10.1016/j.sjbs.2019.02.002

8. Amare, D., & Endalew, W. (2016). Agricultural mechanization: Assessment of mechanization impact experiences on the rural population and the implications for Ethiopian smallholders. Engineering and Applied Sciences, 1(2), 39–48. https://doi.org/10.11648/j.eas.20160102.15

9. Asfaw, S., Shiferaw, B., & Simtowe, F. (2016). Agricultural technology adoption, seed access constraints, and the economic impacts of improved crop varieties in Ethiopia. Food Policy, 59, 1–12. https://doi.org/10.1016/j.foodpol.2016.02.003

10. Ashraf, M., Ullah, L., Shuvro, M. A., & Salma, U. (2019). Transition from millennium development goals (MDGs) to sustainable development goals (SDGs): Blueprint of Bangladesh for implementing the sustainable development goals (SDGs) 2030. Medicine Today, 31(1), 46–59. https://doi.org/10.3329/medtoday.v31i1.40323

11. Awal, M. A. (2022). Rain and flood characteristics, agricultural damages and coping strategies in North-eastern Haor region of Bangladesh. Discovery. 58(324):1274-1296.

12. BBS. (2020). Agriculture Sample Census 2020. Statistics and Informatics Division, Bangladesh Bureau of Statistics, Ministry of Planning, Government of the People's Republic of Bangladesh.

13. BBS. (2020). Yearbook of agricultural statistics of Bangladesh 2020. Bangladesh Bureau of Statistics, Ministry of Planning, Government of the People's Republic of Bangladesh.

14. BBS. (2018). Report on agriculture and rural statistics. Statistics and Informatics Division, Bangladesh Bureau of Statistics, Ministry of Planning, Government of the People's Republic of Bangladesh.

15. Bhusal, A., Khatri, L., Bhandari, B., Sherpa, L., & Neupane, G. (2020). Climate-smart agriculture (CSA): Training manual. Local Initiatives for Biodiversity, Research and Development (LI-BIRD) and Ministry of Land.

16. Biswas, J. K., Kabir, M. S., Rahman, M. S., Nahar, K., & Hasanuzzaman, M. (2019). Managing abiotic stresses with rice agriculture to achieve sustainable food security: Bangladesh perspective. In Advances in rice research for abiotic stress tolerance (pp. 23–45). Woodhead Publishing. https://doi.org/10.1016/B978-0-12-814332-2.00002-2

17. Bite, R. K., Mankar, D. M., & Lambe, S. P. (2013). Knowledge of the Farmers Regarding Farm Tools and Machineries. International Multidisciplinary Research Journal, 2(1), 1-10.

18. Boretti, A., & Rosa, L. (2019). Reassessing the projections of the World Water Development Report. Clean Water, 2(1), 15. https://doi.org/10.1038/s41545-019-0039-9

19. Brammer, H. (2014). Climate change, sea-level rise and development in Bangladesh. FAO AGRIS - International System for Agricultural Science and Technology.

20. Carolan, M. (2017). Publicising food: Big data, precision agriculture, and co-experimental techniques of addition. Sociologia Ruralis, 57(2), 135–154. https://doi.org/10.1111/soru.12120

21. Cook, R. D. (1977). Detection of influential observation in linear regression. Technometrics, 19(1), 15-18.

22. Dally, M., & Newman, L. S. (2021). Worker Health. In Global Climate Change and Human Health: From Science to Practice (p. 203).

23. Department of Agricultural Extension. (2018). Agricultural extension manual (4th ed.). Department of Agricultural Extension, Ministry of Agriculture, Dhaka, Bangladesh.

24. Department of Agricultural Extension. (1999). Agricultural extension manual (Revised ed.). Department of Agricultural Extension, Ministry of Agriculture, Dhaka, Bangladesh.

25. Dey, N. C., Parvez, M., & Islam, M. R. (2021). A study on the impact of the 2017 early monsoon flash flood: Potential measures to safeguard livelihoods from extreme climate events in the haor area of Bangladesh. International Journal of Disaster Risk Reduction, 59, 102247. https://doi.org/10.1016/j.ijdrr.2021.102247

26. Diao, X., Takeshima, H., & Zhang, X. (2020). An evolving paradigm of agricultural mechanization development: How much can Africa learn from Asia? International Food Policy Research Institute.

27. Diao, X., Silver, J., & Takeshima, H. (2016). Agricultural mechanization and agricultural transformation (IFPRI Discussion Paper 01527). International Food Policy Research Institute.

28. Farouque, M. G., Haque, M. M., & Dev, D. S. (2018). Small-scale farmers' attitude and problems regarding one house one farm approach for their livelihoods improvement. International Journal of Agricultural Science, Research and Technology in Extension and Education Systems (IJASRT in EES), 8(4), 191–197.

29. Fuad, M. A. F., & Flora, U. M. A. (2019). Farm mechanization in Bangladesh: A review. International Journal of Research in Business Studies and Management, 6(9), 15–29.

30. Gebiso, T., Ketema, M., Shumetie, A., & Leggesse, G. (2023). Determinants of farm mechanization in central and southeast Oromia region, Ethiopia. Heliyon, 9(7), e18390. https://doi.org/10.1016/j.heliyon.2023.e18390

31. George, D., & Mallery, P., G. D. (2003). SPSS for Windows step by step: A simple guide and reference. 11.0 update (4th ed.). Boston, MA: Allyn & Bacon.

32. Godfray, H. C. J., Aveyard, P., Garnett, T., Hall, J. W., Key, T. J., Lorimer, J., ... & Jebb, S. A. (2018). Meat consumption, health, and the environment. Science, 361(6399), eaam5324. DOI: 10.1126/science.aam5324

33. Goyal, E. R., & Singh, S. (2020). Farm power and machinery management: Cost of operation of farm equipment (pp. 67–69).

34. Gu, D., Andreev, K., & Dupre, M. E. (2021). Major trends in population growth around the world. China CDC Weekly, 3(28), 604.

35. Haque, M. N., Siddika, S., Sresto, M. A., Saroar, M. M., & Shabab, K. R. (2021). Geo-spatial analysis for flash flood susceptibility mapping in the North-East Haor (wetland) region in Bangladesh. Earth Systems and Environment, 5(2), 365–384.

36. Hamid, M. I., Datta, S., & Islam, M. M. (2020). Problems faced by the sub-assistant agriculture officers (SAAOs) working in Department of Agricultural Extension. Research in Agriculture, Livestock and Fisheries, 7(1), 61–73.

37. Hasan, M. F., Rain, M. R. K., Mondol, M. A. S., & Sarmin, S. (2021). Farmers' attitude towards farm mechanization.

38. Hasan, M. F., Rain, M. R. K., Mondol, M. A. S., & Sarmin, S. (2020). Farmers' attitude towards farm mechanization. Bangladesh Journal of Extension Education, 32(2), 41-52.

39. Hasan, M. K., Desiere, S., D'Haese, M., & Kumar, L. (2018). Impact of climate-smart agriculture adoption on the food security of coastal farmers in Bangladesh. Food Security,10, 1073–1088. https://doi.org/10.1007/s12571-018-0824-1

40. Hashanuzzaman, M., Bhowmik, S., Rahman, M. S., Zakaria, M. A., Voumik, L. C., & Mamun, A. A. (2020). Assessment of food safety knowledge, attitudes and practices of fish farmers and restaurants food handlers in Bangladesh. Heliyon, 6(11), e05485. https://doi.org/10.1016/j.heliyon.2020.e05485

41. Hassan, A. W. R., & Das, A. K. (2015). Social issues: Occupation change and food security in Bangladesh. In Food security and risk reduction in Bangladesh (pp. 53–63). https://doi.org/10.1007/978-4-431-55411-0_4

42. Hayran, S., Gul, A., Saridas, M. A., & Donwload, P. (2018). Farmers' sustainable agriculture perception in Turkey: The case of Mersin province. New Medit, 3, 69–78. https://doi.org/10.30682/nm1803f

43. Hoque, M. J. (2020). Rice farmers' perception on occupational risk exposure to pesticides in Bangladesh. Journal of Agriculture, Food and Environment (JAFE), 1(4), 41–47. http://doi.org/10.47440/JAFE.2020.1407

44. Hoq, M. S., Raha, S. K., & Hossain, M. I. (2021). Livelihood vulnerability to flood hazard: Understanding from the flood-prone Haor ecosystem of Bangladesh. Environmental Management, 67, 532–552.

45. Hossen, M. A. (2019). Mechanization in Bangladesh: Way of modernization in agriculture. International Journal of Engineering Trends and Technology, 67(9), 69–77.

46. HIES. (2022). Bangladesh Bureau of Statistics. Household Income and Expenditure Survey, Ministry of Planning, Government of People's Republic of Bangladesh, Dhaka, Bangladesh.

47. Islam, M. N., Atiqul Haq, S. M., Ahmed, K. J., & Best, J. (2022). How do vulnerable people in Bangladesh experience environmental stress from sedimentation in the haor wetlands? An exploratory study. Water Resources Research, 58(7), e2021WR030241. https://doi.org/10.1029/2021WR030241

48. Islam, A. K. M. S. (2018). Status of rice farming mechanization in Bangladesh. Journal of Bioscience and Agriculture Research, 17(1), 1386–1395. https://doi.org/10.18801/jbar.170118.171

49. Jannuzi, F. T., & Peach, J. T. (2019). The agrarian structure of Bangladesh: An impediment to development. Routledge.

50. Kabir, M. S., Salam, M. U., Islam, A. K. M. S., Sarkar, M. A. R., Mamun, M. A. A., Rahman, M. C., & Rahman, N. (2020). Doubling rice productivity in Bangladesh: A way to achieving SDG 2 and moving forward. Bangladesh Rice Journal, 24(2), 1–47. https://doi.org/10.3329/brj.v24i2.53447

51. Kabir, M. J., Kabir, M. S., Salam, M. A., Islam, M. A., Omar, M. I., Sarkar, M. A. R., & Mandal, M. A. (2020). Harvesting of Boro paddy in haor areas of Bangladesh: Interplay of local and migrant labour, mechanized harvesters and COVID-19 vigilance in 2020.

52. Kabir, M. H., Rahman, M. A., & Hasan, M. A. (2019). Factors affecting the use of agricultural machinery in lowland Bangladesh. Bangladesh Journal of Agricultural Economics, 42(1), 59–72

53. Kamruzzaman, M., & Shaw, R. (2018). Flood and sustainable agriculture in the Haor basin of Bangladesh: A review paper. Universal Journal of Agricultural Research, 6(1), 40–49.

54. Khushi, H., Moniruzzaman, M., & Tabassum, N. (2019). Farmers' attitudes towards rice production in selected areas of Mymensingh District. Bangladesh Journal of Agricultural Economics, 39(454-2020-1349), 61–71.

55. Kc, K. B., Dias, G. M., Veeramani, A., Swanton, C. J., Fraser, D., Steinke, D., & Fraser, E. D. (2018). When too much isn't enough: Does current food production meet global nutritional needs? PLOS ONE, 13(10), e0205683. https://doi.org/10.1371/journal.pone.0205683

56. Kelemu, F. (2015). Agricultural mechanization in Ethiopia: Experience, status and prospects. Ethiopian Journal of Agricultural Sciences, 25(1), 45–60. https://doi.org/10.3390/agriculture7060050

57. Lal, R. (2016). Feeding 11 billion on 0.5 billion hectare of area under cereal crops. Food and Energy Security, 5(4), 239–251. https://doi.org/10.1002/fes3.99

58. Lanz, B., Dietz, S., & Swanson, T. (2018). Global economic growth and agricultural land conversion under uncertain productivity improvements in agriculture. American Journal of Agricultural Economics, 100(2), 545–569. https://doi.org/10.1093/ajae/aax078

59. Lambe, S. P., Wakle, P. K., & Gomase, A. S. (2014). Attitude of farmers towards use of combine harvester. The Indian Society of Extension Education, 50(1,2), 93–95.

60. Likert, R. (1932). A technique for the measurement of attitudes. Archives of Psychology, 22 (140), 55.

61. Lyngdoh, D. R., & Mazhar, S. H. (2020). Attitude of farmers towards the use of agricultural machineries in East Khasi Hills District of Meghalaya. Asian Journal of Agricultural Extension, Economics & Sociology, 40(10), 190–194. https://doi.org/10.9734/AJAEES/2022/v40i1031059

62. Makate, M., Nelson, N., & Makate, C. (2018). Farm household typology and adoption of climate-smart agriculture practices in smallholder farming systems of southern Africa. African Journal of Science, Technology, Innovation and Development, 10(4), 421–439. https://doi.org/10.1080/20421338.2018.1471027

63. Mir, M. S., Naikoo, N. B., Kanth, R. H., Bahar, F. A., Bhat, M. A., Nazir, A., & Ahngar, T. A. (2022). Vertical farming: The future of agriculture: A review. The Pharma Innovation Journal, 11(2), 1175–1195.

64. Mim, T. S., & Ansari, M. N. A. (2021). Community based assessment of the changes of provisioning ecosystem services of Aral Haor of Sylhet District. International Journal of Social Science and Human Research, 4(9), 2356–2363. https://doi.org/10.47191/ijsshr/v4-i9-13

65. MWR. (2012). Master plan of Haor area: Volume I. Bangladesh Haor and Wetland Development Board, Ministry of Water Resources, Government of the People's Republic of Bangladesh.

66. Mujeri, M. K., & Mujeri, N. (2021). Bangladesh's rural transformation. In Structural transformation of Bangladesh economy: A South Asian perspective (pp. 117–170).

67. Mondal, M. S. H. (2019). The implications of population growth and climate change on sustainable development in Bangladesh. Jàmbá: Journal of Disaster Risk Studies, 11(1), Article a535. https://doi.org/10.4102/jamba.v11i1.535

68. Nahar, N., Sultana, N., & Miah, J. (2018). Seasonal land cover changes and its effects on essential services of haor and non-haor areas of Kishoreganj district, Bangladesh. Asia- Pacific Journal of Regional Science, 2(2), 399–429. https://doi.org/10.1007/s41685-017-0067-8

69. Nandwani, D., Jamarkattel, D., Dahal, K. R., Poudel, R., Giri, S., & Joshi, T. N. (2021). Attitudes of fruit and vegetable farmers towards organic farming in Kathmandu Valley, Nepal. Sustainability, 13(7), 3888. https://doi. org/10.3390/su13073888

70. Nazif, A., Mohammed, N. I., Malakahmad, A., & Abualqumboz, M. S. (2016). Application of stepwise regression analysis in predicting future particulate matter concentration episode. Water, Air, & Soil Pollution, 227(117). https://doi.org/10.1007/s11270-016-2823-1

71. Negrete, J. C. (2018). Agricultural mechanization: Key to recovery of agriculture of developing countries. Acta Scientific Agriculture, 2, 168–169.

72. Nepal, R., & Thapa, G. B. (2009). Determinants of agricultural commercialization and mechanization in the hinterland of a city in Nepal. Applied Geography, 29(3), 377-389.

73. Ntawuruhunga, D., Affognon, H. D., Fiaboe, K. K., Abukutsa-Onyango, M. O., Turoop, L., & Muriithi, B. W. (2020). Farmers' knowledge, attitudes and practices (KAP) on production of African indigenous vegetables in Kenya. International Journal of Tropical Insect Science, 40, 337–349.

74. Oke, J., Akinkunmi, W. B., & Etebefia, S. O. (2019). Use of correlation, tolerance and variance inflation factor for multicollinearity test. GSJ, 7(5), 652-659.

75. Oo, S. P., & Usami, K. (2020). Farmers' perception of good agricultural practices in rice production in Myanmar: A case study of Myaungmya District, Ayeyarwady Region. Agriculture, 10(7), 249. https://doi.org/10.3390/agriculture10070249

76. Omulo, G., Daum, T., Köller, K., & Birner, R. (2024). Unpacking the behavioral intentions of 'emergent farmers' towards mechanized conservation agriculture in Zambia. Land use policy, 136, 106979.

77. Osemeke, R. F., Igabari, J. N., & Christian, N. D. (2024). Detection and correction of violations of linear model assumptions by means of residuals. Journal of Science Innovation and Technology Research. Vol 3, 139. https://africanscholarpub.com/ajsitr/article/view/139

78. Parvez, S., & Byron, R. K. (2020). Farm mechanization gets a big push from govt. https://www.thedailystar.net/business/news/farmmechanisation-gets-bigpushgovt-1930645 (cited on 15 July 2020).

79. Patil, V., & Veettil, P. C. (2024). Farmers' risk attitude, agricultural technology adoption and impacts in Eastern India. Agriculture & Food Security, 13(1), 50. https://doi.org/10.1186/s40066-024-00497-x

80. Patil, S. D., & Nalawade, S. M. (2019). Dimensions and Determinants of Farm Mechanization in Irrigated Area of. Western Maharashtra, International Journal of Extension Education, 15, 140-148.

81. Patil, S. D. (2018). Factors affecting farm mechanization in rainfed area of Western Maharashtra in India. Young (Up to 31 years), 31, 21–53.

82. Pretty, J. (2013). Agri-culture: Reconnecting people, land and nature. Taylor & Francis.

83. Poddera, S. K., Rahmanb, S. M. A., Hoquea, M. J., Mithuna, M. N. A. S., & Billahc, M. M. (2022). Exploring farmers' attitudes towards yield gap minimization of rice: A case from Mymensingh district, Bangladesh. https://doi.org/10.26480/seps.01.2022.14.20

84. Rahman, M. M. (2021). Achieving sustainable development goals of Agenda 2030 in Bangladesh: The crossroad of the governance and performance. Public Administration and Policy, 24(2), 195–211. https://doi.org/10.1108/PAP-12-2020-0056

85. Rahman, M. Z., Afrin, M. F., Akter, M., & Hasan, M. (2021). Need for capacity development of farmers towards efficient use of farm machineries. International Journal of Tropical Agriculture, 39, 159–168.

86. Rahman, A., Ali, R., Kabir, S. N., Rahman, M., Al Mamun, R., & Hossen, A. (2020). Agricultural mechanization in Bangladesh: Status and challenges towards achieving the sustainable development goals (SDGs). AMA, Agricultural Mechanization in Asia, Africa and Latin America, 51(4), 106–120.

87. Rahman, M. S., Haque, M. M., Kabir, M. J., Islam, A. K. M. S., Sarkar, M. A. R., Mamun, M. A. A., & Kabir, M. S. (2020). Enhancing rice productivity in the unfavorable ecosystems of Bangladesh. Bangladesh Rice Journal, 24(2), 83–102. https://doi.org/10.3329/brj.v24i2.53450

88. Rahman, M. S., Ali, R., & Hosain Oliver, M. (2017). Farm mechanization in Bangladesh: A review of the status, roles, policy and potentials. Journal of Agricultural Engineering, 19(1), 45–58. https://doi.org/10.2499/9780896293809_07

89. Rahman, S., & Salim, R. (2013). Six decades of total factor productivity change and sources of growth in Bangladesh agriculture (1948–2008). Journal of Agricultural Economics, 64(2), 275–294. https://doi.org/10.1111/1477-9552.12009

90. Ramana, C., & Kumari, P. L. (2019). Farmers' perception and usage of farm machinery in Southern Zone of Andhra Pradesh. Journal of Pharmacognosy and Phytochemistry, 8(5), 751-759.

91. Rana, M. M., Farouque, M. G., & Rahman, M. Z. (2020). Attitude of common interest group members towards national agricultural technology programme (phase-I) interventions. Journal of the Bangladesh Agricultural University, 18(1), 194–202. https://doi.org/10.5455/JBAU.94764

92. Repon, M., & Russel, A. (2014). Problems and prospects of agricultural change on efforts to development in rural areas of Bangladesh (Doctoral dissertation, University of Rajshahi). http://103.79.117.116/bitstream/handle/123456789/712/D3781.pdf?sequence=1&isAll owed=y

93. Reza, M. S., Hossain, M. I., & Hossain, M. E. (2020). Environmental challenges and the measures taken by the BMDA for sustainable agriculture and environment in the Barind Tract, North-West of Bangladesh. Economics, 5(5), 197–209. https://doi.org/10.11648/j.ijae.20200505.17

94. Rouf, K. A. (2019). Grameen Krishi Foundation (GKF) and its donor's contribution to deep tube-well irrigation-based rural agricultural community development in Northern Bangladesh.

95. Sanaullah, A. B., & Ullah, I. (2021). Challenges and prospects of farm mechanization in Pakistan: A case study of rural farmers in District Peshawar Khyber Pakhtunkhwa. Sarhad Journal of Agriculture, 37(1), 167-179. http://dx.doi.org/10.17582/journal.sja/2021/37.1.167.179

96. Sharmin, A., Hossain, M., & Mollick, A. S. (2021). Farmers' perceptions and attitudes toward aquasilviculture in the periphery of the Sundarbans Forest of Bangladesh. Small-Scale Forestry, 20, 391–405. https://doi.org/10.1007/s11842-021-09473-w

97. Sheheli, S., Akter, S., Hasan, M. M., & Hasan, M. J. H. K. (2023). Knowledge of fish farmers on using artificial feed for catfish culture. International Journal of Fisheries and Aquatic Studies, 11(5), 120–129. https://doi.org/10.22271/fish.2023.v11.i5b.2856

98. Shyama, S. P., Rahman, M. A., Khan, M. A., & Akter, T. (2022). Assets possession and food consumption level of haor people in a selected area of Bangladesh. Archives of Agriculture and Environmental Science, 7(2), 246–254. https://doi.org/10.26832/24566632.2022.0702013

99. Sims, B., & Kienzle, J. (2017). Sustainable agricultural mechanization for smallholders: What is it and how can we implement it? Agriculture, 7(6), 50. https://doi.org/10.3390/agriculture7060050

100. Sims, R., Flammini, A., Puri, M., & Bracco, S. (2015). Opportunities for agri-food chains to become energy-smart. FAO USAID.

101. Skinner, B. F. (1953). Science and Human Behavior. New York: Macmillan.

102. Sohel Rana, M. H. H., Alam, M. S., & Islam, M. S. (2017). Farmer attitude towards organic vegetable cultivation in Rangunia Upazila, Chittagong, Bangladesh. Journal of Bioscience and Agriculture Research, 14(01), 1151–1156. https://doi.org/10.18801/jbar.140117.141

103. Sourav, A., & Abdullah, M. (2017). Impact of flash flood on boro rice production in Taherpur upazila.

104. Sojib, M. R., Rahman, M. Z., & Farouque, M. G. (2022). Farmers' perception of environmental effects owing to transformation of cropland into industrial uses: A study of an industry dominated area in Bangladesh. In Sustainable Agricultural Innovations for Resilient Agri-Food Systems (p. 121). https://doi.org/10.55362/IJE/IESIC/2022/PROC

105. Sultana, S., Jui, K. F., Moushumy, N. S., Siddika, H., & Rahman, M. A. (2023). An analysis of income sources and food security status in haor regions of Kishoregonj district, Bangladesh. Asian Journal of Economics, Business and Accounting, 23(19), 145–156. https://doi.org/10.9734/AJEBA/2023/v23i191079

106. Sylvester, G. (Ed.). (2018). E-agriculture in action: Drones for agriculture. Food and Agriculture Organization of the United Nations & International Telecommunication Union.

107. Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. International journal of medical education, 2, 53.

108. Uddin, M. N., Kabir, K. H., Roy, D., Hasan, M. T., Sarker, M. A., & Dunn, E. S. (2021). Understanding he constraints and its related factors in tilapia (Oreochromis sp.) fish culture at farm level: A case from Bangladesh. Aquaculture, 530, 735927. https://doi.org/10.1016/j.aquaculture.2020.735927

109. Van Schendel, W. (2020). A history of Bangladesh. Cambridge University Press.

110. Van Loon, J., Woltering, L., Krupnik, T. J., Baudron, F., Boa, M., & Govaerts, B. (2020). Scaling agricultural mechanization services in smallholder farming systems: Case studies from sub-Saharan Africa, South Asia, and Latin America. Agricultural Systems, 180, 102792. https://doi.org/10.1016/j.agsy.2020.102792

111. Vasileiou, K., Barnett, J., Thorpe, S., & Young, T. (2018). Characterising and justifying sample size sufficiency in interview-based studies: Systematic analysis of qualitative health research over a 15-year period. BMC Medical Research Methodology, 18(1), 1–18. https://doi.org/10.1186/s12874-018-0594-7

112. Watson, J. B. (1913). Psychology as the behaviorist views it. Psychological Review, 20(2), 158–177.

113. Wikipedia. (2025). Districts of Bangladesh. https://en.wikipedia.org/wiki/Districts_of_Bangladesh

114. Yousuf Haroon, A. K., & Kibria, G. (2017). Wetlands: Biodiversity and livelihood values and significance with special context to Bangladesh. In Wetland science: Perspectives from South Asia (pp. 317–346).

115. Yucer, A. A., Kan, M., Demirtas, M., & Kalanlar, S. (2016). The importance of creating new inheritance policies and laws that reduce agricultural land fragmentation and its negative impacts in Turkey. Land Use Policy, 56, 1–7. https://doi.org/10.1016/j.landusepol.2016.04.029

116. Zhang, S., Sun, Z., Ma, W., & Valentinov, V. (2020). The effect of cooperative membership on agricultural technology adoption in Sichuan, China. China Economic Review, 62, 101334. https://doi.org/10.1016/j.chieco.2019.101334