

The AI-Driven Future of Mobile Finance: Understanding User Perceptions in Bangladesh

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ABSTRACT

This paper investigates the relationship between user perception factors and AI-driven user experience in Bangladeshi mobile financial services. Two factors for AI-driven user experience (AI-hedonic user experience and AI-recognition user experience) and five factors for user perception—user-friendliness, personalization, trust, relationship commitment, and user satisfaction—are used in the research. The population of this study was the users of the MFS industry in Bangladesh. The study comprises 226 respondents, using a convenience sampling technique. The study showed that three user perception variables—user-friendliness, relationship commitment, and user satisfaction—positively and significantly affected AI-driven hedonic and recognition user experiences. Alone, the trust generated a positive, significant impact on AI-driven hedonic user experiences. Personalization, however, was found to have no substantial or positive effect on the hedonic, recognition, and AI-driven user experiences among Bangladeshi MFS users. Therefore, mobile financial organizations should increase customer trust and implement more customized AI-driven solutions to enhance brand competency and gain a sustainable competitive advantage.

KEYWORDS: Mobile Financial Services (MFS), Artificial Intelligence (AI), AI-driven User Experience, AI-Hedonic User Experience, AI-Recognition User Experience

1. Introduction

Financial institutions that provide mobile financial services are compelled to establish their presence in the cloud and online, engage with their user base, prompt governments to implement e-government initiatives, and drive their presence on mobile devices and social media because of the

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"Digital Age," which was initiated by the Internet and mobile technologies. E-business, which includes O-signatures, e-invoices, e-commerce, the Internet, mobile banking, and e-payments, is a significant revolution in conducting online business. This revolution significantly improves efficiency in both the corporate and individual realms. The business environment, on the other hand, is compelled to assess big data and respond simultaneously, utilizing CRM systems, as a result of the growing amount of information that is being generated every day. Despite the fact that the digital era, which includes fields such as mechatronics, nanotechnology, and genetics, contributes to "Space Economics." Emerging technologies such as artificial intelligence, semantic analysis, advancements in robotics and mechatronics, big data analytics, cloud computing, and neural networks, along with current trends like social media, will propel the future trajectory of banking and financial services. According to Porter's work "Value Creation and Competitive Advantage Theory" (Porter, 1985), this will force humanity and business sectors, including governments and affiliated organizations, to investigate new opportunities for lowering costs and increasing revenues through increased efficiency and productivity. Porter's theory was articulated in his work. Companies can achieve increased profitability and sustainability only through the implementation of two strategies: either the reduction of costs or the enhancement of value.

Artificial intelligence (AI) is a vast and varied field, encompassing a number of subfields that focus on various aspects of intelligence simulation. Due to the fact that artificial intelligence (AI) is set to drastically revolutionize the interactions between machines and humans (Paschen, 2019), computers will be able to make effective decisions with minimum or no intervention from humans (Duan & Dwivedi, 2019; Park & Park, 2003). Artificial intelligence (AI) is defined by Lopez and Casillas (2013) as computer systems that are capable of developing feasible automated solutions for challenges that typically require human intellect. It is becoming increasingly evident that artificial intelligence is a crucial force that has the potential to disrupt corporate environments. It is becoming increasingly apparent that artificial intelligence is a critical force that has the potential to disrupt corporate environments. Studies by Dadouchi & Agard, 2018; Davenport, 2020; Dwivedi, 2021 Pillai et al., 2020 and Wilson et al. 2019 have found that artificial intelligence has the potential to significantly enhance the operations of existing companies and facilitate the establishment of new businesses. Some people believe that the employment of platforms that are enhanced with artificial intelligence could potentially reduce these risks and increase user feedback (Zaki, 2021).

Due to the fact that users are not accustomed to technology-mediated connections (such as the utilization of platforms that are enhanced with artificial intelligence), it is essential to determine how prepared they are and what their thoughts are about the sharing of personal information as the initial stage in the process of establishing limitations (Dyussebayeva, 2020). The overall number of mobile phone subscribers in Bangladesh reached 188.78 million at the end of November 2024, according to the Association of Mobile Telecom Operators of Bangladesh (AMTOB)², which reported the data. The mobile Financial Services (MFS) sector in Bangladesh is experiencing annual growth due to the increased accessibility of digital financial products and services. Those who provide

² <https://www.amtob.org.bd/home/industrystatics>

Mobile Financial Services (MFS) are necessary for Bangladesh to progress in its transformation to a digital economy. Through this initiative, a sizeable part of formerly unbanked and economically disadvantaged areas have been successfully integrated into the official banking system. These populations, which may have been located in either rural or urban areas, have historically been denied access to the services offered by regular financial institutions. When it comes to the digital era, mobile financial services (MFS) are not a new concept. It has been spread all over the world. The Mobile Financial Service (MFS) is a digital wallet that enables users to send funds to other members using their mobile phones in a way that is quick, easy, and confidential.

There is no need for an intermediary because the transactions are carried out online. This means that mobile money services are available for all cell phone subscribers. In 2012, Dutch Bangla Bank Limited became the first financial institution in the country to offer mobile banking services, marking the beginning of a project that would last for ten years. To further the goal of increasing financial inclusion for all individuals, the central bank has begun the process of issuing licenses for mobile financial services. A total of ten financial institutions and three related organizations are currently providing Mobile Financial Services (MFS) as an extra payment method. The MFS providers are Rocket, bKash, MYCash, Islami Bank mCash, Trust Axiata Pay (tap), FSIBL FirstPay SureCash, Upay, OK Wallet, Rupali Bank SureCash, TeleCash, Islamic Wallet, Meghna Pay, and Nagad.

2. Literature Review

Many people in Bangladesh use MFS to share and receive money, pay their bills, top up their phones, and pay for things they buy (Lee et al., 2021). When families have domestic migrants, the chance of using MFS goes up by about 43%, but women are less likely to use it than men (Akhter & Khalily, 2020). Few research has examined Bangladeshi users' perceptions of Mobile Financial Services (MFS). Also, nowadays, banks have used AI to provide better service to their customers (e.g., providing services and products according to individual needs, detecting new business prospects, forecasting and detecting risk and fraud, and restructuring tasks). According to Gupta et al. (2021), their study looked into how incorporating AI into online shopping on e-commerce sites can improve the user experience. The things that affect the user experience when AI is used. The authors used exploratory factor analysis to find the factors that affected each variable in the model.

Contemporary business professionals have recognized the necessity of using information technology in their industry. Companies can attain greater profitability and sustainability solely through two strategies: cost minimization and value maximization. The advancements in technology and various scientific disciplines, facilitated by their convergence, will aid in achieving these objectives, and further discoveries will emerge in the coming years, resulting in disruptive transformations in business, daily life, and the global economy (Manyika et al., 2013). The research delineated the application of AI in B2B marketing innovation into five domains, highlighting principal trends in the literature and proposing avenues for future inquiry (Han et al., 2021). The notion of artificial intelligence (AI) as a disruptive technology in business has evolved in academic and professional literature in a disorganized and unstructured fashion. Despite organizations dedicating time, effort, and resources to the implementation process, the anticipated advantages of AI may not

materialize (Makarius et al., 2020). Artificial intelligence (AI) encompasses a diverse array of technologies that offer numerous benefits for enterprises, including enhanced economic value (Papagiannidis et al., 2021). Anand Rao, Global Artificial Intelligence Lead at PWC, said that their most recent AI study showed that 86% of businesses were already benefiting from AI by making the user experience better³. Much study has been done to figure out what AI-CRM means for user relationships and, more specifically, what it means for users and stakeholders (Libai et al., 2020). 84% of users told Salesforce that the way a business treats them is just as important as its goods and services. Users are very important to any business, and studies are being done to find out how AI tools can help improve the user experience (Sujata et al., 2019).

Ameen et al. (2020) showed in their study how AI can improve the user experience in online beauty and how retailers can benefit from this. Mobile banking, which is the same thing as mobile financial services (MFS), is the use of a smartphone or other mobile device to do online banking tasks like checking account balances, transferring funds, receiving funds, paying bills, and finding ATMs without being in a certain place (Tracy, 2020; Hawrylack, 2021). In 2021, bKash is the biggest MFS in Bangladesh, with a 48% market share. Nagad is in second place, with a 28% market share⁴. There were 87.197 million active MFS accounts in October 2024, which is 36.995% of the total registered MFS users. Out of all the transactions that happened that month, 452.31989 billion were cash in, 487.88349 billion were cash out, 76.6735 billion were merchant payments, and 6.0614 were government payments. The total number of registered MFS users and active accounts with their growth rates are shown in Table 1.

Table 1: Number of registered MFS Users' and Active Accounts⁵

Year	Total No. of Registered MFS Users (Million)	Growth Rate (%)	Total Active Accounts (Million)	Growth Rate (%)
2021	109.627	—	40.064	—
2022	188.574	41.87	56.559	29.16
2023	220.086	14.32	82.498	31.44
2024	235.705	6.63	87.197	5.39

According to Bashir & Muhammad (2023), their study has shown that mobile financial services greatly correlate with social influence, performance expectation, risk perception, and trust view and thus support financial inclusion. The study has also found that the more contact of mobile banking consumers with devices corresponds with the expansion of mobile financial services, acceptance of technical advancements, and a higher possibility of adoption.

³ Forbes report, 2020. <https://www.forbes.com/sites/tomtaulli/2020/12/12/artificial-intelligence-ai-whats-in-store-for-2021/>

⁴ The Daily Star Report, 2021. <https://www.thedailystar.net/supplements/mfs-and-financial-inclusion-bangladesh/news/how-mobile-money-reshaping-financial-inclusion-bangladesh-3529986>

⁵ Bangladesh Bank, <https://www.bb.org.bd/en/index.php/financialactivity/mfsdata>

A study by Himel et al. (2021) found that consumers' opinions on the acceptance of mobile financial services (MFS) depend much on perceived utility (PU), perceived ease of use (PEOU), and perceived trust (PT). Furthermore, affecting consumers' attitudes and intentions to utilize are the adoption's challenges. Though perceived ease of use, self-efficacy, and expenditures are not very important, perceived usefulness and trust are the main drivers of attitude. This study has provided insightful analysis to financial institutions, service providers, and authorities, and it has improved understanding of MFS adoption inside local communities (Hayat & Kashem, 2024). The results of the study have shown that consumer satisfaction is mostly influenced by perceived utility, followed by perceived safety and regarded simplicity of use. Successful influence on both continuity intention and referral intention is provided by customer contentment, followed by perceived usefulness and personal creativity (Ahmed et al., 2022). Researchers have discovered that during the COVID-19 epidemic, users' perceived risk, performance expectation, and effort expectation all influenced how much they valued MFS platforms.

However, users' plans to use mobile financial services (MFS) platforms are strongly linked to social influence, perceived trust, and perceived value. The study findings have shown that customers' propensity to use MFS systems during the outbreak is unaffected by their perceived risk (Yan et al., 2021). As Akturan and Tezcan (2012) have said, perceived usefulness, perceived social risk, and perceived attitudes towards mobile banking are influenced by performance risk and perceived advantage; perception is the main determinant of utilizing mobile banking. Moreover, no direct link exists between the financial risk, temporal risk, perceived simplicity of use and disposition, perceived utility and use intention, attitudes, and security and privacy threats that are noted. Hassan et al. (2014) have focused on the factors influencing the Mobile banking services that are being implemented in Bangladesh. They have assessed five criteria: apparent value, Subjective norms, perceived simplicity of use, perceived trustworthiness, and consumer mobile banking knowledge, which are all important factors. There are potential risks associated with using mobile banking services.

The study has shown that consumers' approval of mobile banking services is influenced by these parameters significantly and favorably, as Kweyu and Ngare (2013) have observed a factor analysis of customer impressions and have investigated the variables driving Kenyan mobile banking service adoption. The focus is on Kenyan banking products. The study has shown that demographic factors and consumer views might have different impacts. The findings of the study have shown no notable differences in the impression of risk of use and ease of use between genders in the decision-making process. According to Tulcanaza-Prieto et al. (2023), their study has shown five segments for user perception: ease of use, personalization, trust, user loyalty, and user satisfaction. It also had two sections for AI-enabled user experience: AI-hedonic user experience and AI-recognition user service. To sum up, the study has shown that all five factors affecting how users feel have a positive and significant effect (at least at the 5% level) on AI-enabled user experience, AI-hedonic user experience, and AI-recognition user service in the Ecuadorian banking industry.

Based on the above literature reviews, the following users' perception factors are found. As no literature has investigated important factors of users' perception that influence AI-driven user experience for Mobile Financial Services (MFS) in Bangladesh, thus the study concentrated on a single, significant research challenge based on the research gap: What factors influence AI-driven user experience for Mobile Financial Services (MFS) in Bangladesh? Here, user-friendliness, personalization, trust, relationship commitment, and user satisfaction are the five users' perception factors. AI-driven user experience has two parts: AI-hedonic user experience and AI-recognition user experience.

3. Motivation of the Study

This study has been perceived, conceptualized, and driven toward implementations through some academic factors, emerging technologies, and their practical implications. Most of the research focused on how companies utilized the AI. Insufficient empirical research exists to understand how AI in mobile financial services may improve the user experience. Mobile financial services research is scarce, indicating possibilities for additional study. The utilization of AI signifies enhancements in marketing strategies and offerings that are capable of swiftly discerning the preferences of economic agents (Kartemo & Helkkula, 2018). Artificial intelligence can replicate intuitive and empathetic jobs by developing cognitive neural networks that can discern user personalities and engage with individuals to generate value (Kucharska, 2019; Hair et al., 2010). Mujeri and Azam (2018) have found numerous major and noteworthy factors that influence economic inclusion in Bangladesh for mobile financial services. Many requirements are necessary to maintain the quality and variety of MFS products: (i) the invention of MFS products, (ii) a competitive ecosystem enabling market accessibility, and (iii) better quality services providing value for money.

The research goal for this study is to identify the factors that influence user perception in the mobile financial services sector, specifically their experience with AI-powered virtual/mobile applications and how this AI-driven user experience changes user perception. This study offers crucial insights for MFS managers, as user perceptions and opinions regarding AI financial services provided by MFS favorably impact the AI-driven user experience. This research offers a comprehensive analysis of the essential aspects of user perception that influence the AI-driven user experience. This study will guide representatives and managers in the mobile financial service sector in formulating and executing a strategic plan incorporating AI technology into their financial goods and services. Furthermore, it offers empirical evidence regarding the factors users favor when utilizing virtual/mobile applications and accessing digital services in the mobile financial service sectors.

4. Objectives of the Study

The main objective of this study is to identify the users perception factors that influence AI-driven user experience for mobile financial services (MFS) in Bangladesh. The specific objectives of this study were as follows:

- i. To identify the demographic profiles of the active virtual app users of mobile financial services (MFS) in Bangladesh.

- ii. To identify the relationship between user perception factors and AI-driven user experience in Bangladesh's MFS sector.
- iii. To recommend and provide some suggestions for future studies.

5. Description of the Factors and Hypothesis Development

5.1 Users Perception Factors

Interactive information retrieval systems are evaluated using user behavior and perception criteria. User perception includes understanding cloud e-learning applications' appearance, activities, content, and technological features. User perception is usually associated with satisfaction, usability, and post-interaction evaluations of certain events, systems, or activities (Zhuang et al., 2016). A person's opinion of a company is called user perception. The user perception component includes user-friendliness, personalization, trust, relationship commitment, and user satisfaction. (Cheriyen et al., 2022; Ameen et al., 2021 ; Sanjuk et al.,2020 ; Jarek & Mazurek, 2019; Zhen et al., 2017 ; Colwell, 2008)

User-friendliness means clients save time and effort when buying and using services (Berry et al., 2002). User-friendliness design reduces user effort. For example, a chatbot interacting with a user instantly upon accessing the virtual/mobile app is convenient. Some chatbots are intelligent enough to refuse to answer a client's question based on the tone of the discussion, effortlessly redirecting the user to a human agent. The user is ignorant, but convenient technology has been invented. Instead of asking for identification, a company can use speech recognition to identify and authenticate users. User service comfort can be improved in several ways. User service agent response time is a major convenience factor. Due to their 24/7 accessibility, AI-driven services reduce users' sacrifice. **Personalization** refers to the provision of customized information that aligns with a user's desires and preferences and fosters a positive consumption experience (Bilgihan et al., 2016). Prior studies demonstrate that personalizing AI-driven services enhances brand competency, user perceptions of quality, sensitivity to user sacrifice, and favorable firm attributions, thereby cultivating client trust in the brand and the business. (Aguirre et al., 2015; Shen & Dwayne, 2009; Komiak & Benbasat, 2006).

Trust necessitates robust benevolence, product reliability, and service integrity. It depends on client benefits and confidence in a company's product or service assertions. Users disclose their personal information because they trust in confidentiality, which enhances the user-firm relationship (Ponder et al., 2016). E-commerce trust includes both brand integrity and technological reliability. Companies must meticulously consider their management of client data throughout digital interactions (Tulcanaza-Prieto & Morocho-Cayamcela, 2021). Prior research indicated that AI needs confidence. It guarantees product or service acceptance, enhances productivity through advancement, stimulates corporate innovation, and fosters technological development (Siau & Wang, 2018). Recent dimensions of trust in AI-driven user service encompass technology and understanding, brand identity, and purpose (confidence in intentions) (Henseler et al., 2015; Lee &

See, 2004;). The relationship between the brand and the user is contingent upon the user's experience and trust, which is advantageous for both current and future interactions (Keiningham et al., 2017; Hengstler et al., 2016). AI in user experience reduces fraud through technological automation and cyber security, identifies user needs and behaviors for better targeting, and analyzes industry data using machine learning applications, boosting firms' competitive advantage and **relationship commitment**. AI techniques that improve perceived value, cognitive trust, affective trust, and client satisfaction, which are all influenced by service quality in information systems, can increase relationship commitment and improve the AI-driven user experience. (Chen et al., 2023; Chen et al., 2022; Yau et al., 2021)

User satisfaction is the difference between product or service performance, realization or injustice, and expectations or confirmation (Xu et al., 2007). This study measures post-purchase user behavior and satisfaction, including the service environment (Krystallis & Chrysochou, 2014). AI can improve user engagement, increase upsell and cross-sell opportunities, and lower the cost of service. It has been shown that an AI-driven user experience enhances business performance and user satisfaction (Javed & Cheema, 2017; Sayani, 2015).

5.2 AI-driven User Experience

Modern technologies and AI can help mobile financial service sectors handle client data. One can predict user emotions, preferences, and brand engagements by analyzing user surveys, emails, and social media interactions (Oh et al., 2012). Artificial intelligence (AI) technologies like machine learning and natural language processing can help merchants improve user satisfaction by emphasizing their competitive advantages. This will enhance user satisfaction. Prior research has identified at least four components that makeup user experiences: cognitive perception (e.g., functionality, speed, and service availability), emotional response (e.g., positive or negative sentiments elicited by the service), physical and sensory interaction (e.g., lighting, layout, signage, technological attributes, intuitive design, and user-friendliness interface), and social influences. AI tools analyze profiles, preferences, and prior user interactions to improve user-manager communication and forecast future consumption patterns. Since AI-driven experiences interact and integrate, they may enhance the user experience. Hedonic user experience and recognition user experience (HUE and RUE) make up the AI-driven user experience.

Hedonic consumption emphasizes subjective acquisition aspects like sensations, memories, emotions, and imagination. AI may imitate users' perceptions during product or service purchases by providing ratings or comments on their most memorable experiences (Foroudi et al., 2018; Oh et al., 2012; Verhoef et al., 2009). The main barrier to AI integration in economic sectors is human contact, which must be recognized in the digital age. It cannot match the human touch's depth, empathy, comprehension, and emotional bond. AI-hedonic user experience may reflect client views. Technology cannot fully capture the essence of human connection given by touch, the global language for expressing emotions, developing relationships, and improving well-being (Song et al., 2022; Ashfaq et al., 2020). User acknowledgment shows appreciation for a company's users. The company's use of this strategy helps retain loyal and engaged users. Recognition includes safety,

relevance, connection, hospitality, and aesthetics (Foroudi et al., 2018; Rose et al., 2012). A company's client recognition increases user interest in buying its products and services. Corporations can easily gain a competitive edge.

5.3 Hypothesis Development and Research Diagram

A statement that poses a question and offers a prediction is known as a research hypothesis. While new ideas and hypotheses are acknowledged as crucial instruments for scientific advancement, a universally agreed definition or formal framework for categorizing and methodically tracking hypotheses in academic literature is lacking (Karunarathna et al., 2024). In 1973, the U.S. National Library of Medicine established "Research Design" as a structured keyword through its Medical Subject Headings (MeSH). This concept inherently connected hypothesis development to data collection, testing, ethics, methodologies, and standards. Marketing, advertising, reviews, and social media comments affect product perceptions. The AI-driven user experience will be shaped by user-friendliness, personalization, trust, relationship commitment, and user satisfaction. AI is used in all company activities and is praised for improving service quality by capitalizing on user perceptions, preferences, and expectations. AI has the potential to alter users' perceptions of products, services, and brands, influencing their purchasing and payment decisions. Managers may optimize all internal processes using this vital data, which reveals the firm's potential and difficulties and leads to competitive financial ratios. Finally, the last hypotheses (H6, H6a and H6b) covered the many consequences of all factors on the AI-driven user experience. In accordance with the literature review, the study formulates the following hypotheses (Table-2) to gain the specified objective.

Table 2: Hypotheses of the study

Factors Name	Hypothesis	
User-Friendliness (UF)	H1	User-friendliness features will positively impact the AI-driven user experience.
	H1a	User-friendliness features will positively impact the AI-Hedonic user experience.
	H1b	User-friendliness features will positively impact the AI-recognition user experience.
Personalization (PER)	H2	Personalization features will positively impact the AI-driven user experience.
	H2a	Personalization features will positively impact the AI-Hedonic user experience.
	H2b	Personalization features will positively impact the AI-recognition user experience.
Trust (TRU)	H3	Trust features will positively impact the AI-driven user experience.
	H3a	Trust features will positively impact the AI-Hedonic user experience.
	H3b	Trust features will positively impact the AI-recognition user experience.
	H4	Relationship commitment features will positively impact the AI-driven user experience.

Factors Name	Hypothesis	
Relationship Commitment (RC)	H4a	Relationship commitment features will positively impact the AI-Hedonic user experience.
	H4b	Relationship commitment features will positively impact the AI-recognition user experience.
User Satisfaction (US)	H5	User satisfaction features will positively impact the AI-driven user experience.
	H5a	User satisfaction features will positively impact the AI-Hedonic user experience.
	H5b	User satisfaction features will positively impact the AI-recognition user experience.
User Perception Factors (UPF)	H6	User Perception Factors will positively impact the AI-driven user experience.
	H6a	User Perception Factors will positively impact the AI-Hedonic user experience.
	H6b	User Perception Factors will positively impact the AI-recognition user experience.

The following research model indicates the relationship between user perception factors and AI-driven user experience, including AI-hedonic and AI-recognition user experience elements in the Bangladeshi mobile financial services (MFS) sector (Figure 1).



Figure 1: Research Framework (Author work)

6. Methodology, Data Collection & Limitations

Both primary and secondary data are important for conducting research. By using a pre-defined set of survey questionnaires, the researcher can collect the primary data. The researcher has collected the secondary data from various sources, such as articles published in recognized journals, e-

journals, online publications, newspapers, and websites (Ajayi, 2017). In this study, the researcher used both primary and secondary data for collecting the research data. A survey instrument was created based on the research constructs to collect the primary data. The population of this study was active users of the MFS sector in Bangladesh. More quickly and economically feasible, the survey used a convenience sampling approach, including a sample size of 226 people. Table 1 shows the number of registered and active MFS users; yet, it was difficult to identify the people who were actually active MFS virtual application users who knew artificial intelligence. Convenience sampling was therefore chosen because of its simplicity of use and the possibility of finding easily available participants. Participants were asked to articulate their opinions on the incorporation of AI in their virtual or mobile applications. The survey employed a five-point Likert scale and included basic demographic information. The researcher subjected the instrument to pre-testing, and users were excluded from the final sample. Upon completion of the pre-test, the questionnaire was revised to enhance clarity.

The study comprised five constructs related to user perception (user-friendliness, personalization, trust, relationship commitment and user satisfaction), and two constructs pertaining to AI-driven user experience had two parts: AI-hedonic user experience and AI-recognition user experience. The study included 35 items to assess the total seven dimensions, employing a five-point Likert scale for each item, with one indicating strongly disagree and five indicating strongly agree. The researchers developed the scoring range of a 5-point Likert scale of the survey in which 0.1 - 1 shows strongly disagree, 1.1 - 2.0 shows disagree directly, 2.1 - 3.0 shows neutral, 3.1 - 4.0 shows agree, and 4.1 - 5.0 indicates strongly agree. Descriptive statistics (mean value) has been measured to identify the most important factors that influence AI-driven user experiences. Google Forms and IBM SPSS (Statistical Package for the Social Sciences) Statistics 20 were utilized to gather and analyze all questionnaire results. A total of 226 questionnaires were documented. The final sample comprises 220 records, accounting for repeated observations and incorrect responses. This study was comprised of the following subdivisions: demographic analysis, descriptive statistics of the seven dimensions, reliability analysis of the 33 items, validity analysis, correlation analysis, and regression analysis to substantiate the study hypothesis.

There were some limitations in this study. Some respondents were hesitant to give the required information because they were afraid it would be used illegally. This study entirely samples the whole country, so the results may not represent a specific region of Bangladesh. Research with strong or favorable conclusions may be overrepresented in the literature due to journals' preference for publishing such studies. Negative or inconclusive results may not be published in research papers, which can distort the evidence. The way the data for this study was gathered—through online surveys—may have caused some bias in the results. Age, gender, and education are among the particular traits of the target group that could be under-represented or over-represented. Such an event may happen even with a well-organized sample strategy, as this method depends on the participants' will and willingness to interact with the survey. Although it generates probable bias that may affect the external validity of the results, convenience sampling was used due to practical restrictions. One has to consider the small sample size and the use of a convenience sampling technique as limitations on the interpretation of the results. Time and budget constraints necessitated the use of convenience sampling as the only practical solution. One of the main

problems is that some groups may not be reflected in online surveys because of their lack of internet access or inadequate understanding of the subject. The survey questions used in this research were developed for simplicity and clarity in order to handle this last concern. The sampling approach helped to provide a range of responses; nonetheless, many conceivable biases might affect the results. The respondents' knowledge of AI might vary greatly; those who have more technological awareness are probably more optimistic about AI-driven MFS technologies. In order to solve this, the poll included a question on familiarity with artificial intelligence, and the answers were examined suitably. Geographic differences in financial literacy might also affect customers' understanding and use of mobile financial services (MFS). Urban respondents often show more financial knowledge and experience with mobile banking services, therefore perhaps biasing the results. For respondents who have not used the virtual app of MFS or are familiar with AI, the researcher could not collect proper data to meet the secondary objective of this study.

7. Results

7.1 Demographic Analysis

The demographic information analysis was done to identify the respondents' particular characteristics. The characteristics included respondent gender, age distribution, level of education, occupation, income level, whether respondents are familiar with the definition of AI, the number of MFS companies that the respondents frequently use, and whether the MFS company uses AI to design the MFS products and services. The following table shows the demographic information of the mark respondent.

Table 3: Demographic Analysis of the Respondents

Demographic factors		Frequency	Percent	Valid Percent	Cum. Percent	Mean	Std. Deviation
Gender	Male	95	43.2	43.2	43.2	1.57	.496
	Female	125	56.8	56.8	100.0		
Age	18 - 28	164	74.5	74.5	74.5	1.32	.597
	29 - 39	41	18.6	18.6	93.2		
	40 - 50	15	6.8	6.8	100.0		
Level of education	HSC	16	7.3	7.3	7.3	2.68	.709
	Hon's (BS/BBA/BA)	54	24.5	24.5	31.8		
	Master's (MS/MBA/MA)	135	61.4	61.4	93.2		
	Ph.D.	15	6.8	6.8	100.0		
Monthly personal income(Tk)	0 - 10000	105	47.7	47.7	47.7	2.54	1.854
	10001 - 20000	32	14.5	14.5	62.3		
	20001-30000	16	7.3	7.3	69.5		

Demographic factors		Frequency	Percent	Valid Percent	Cum. Percent	Mean	Std. Deviation
	30001-40000	22	10.0	10.0	79.5		
	40001 - 50000	16	7.3	7.3	86.8		
	Above 50000	29	13.2	13.2	100.0		
Occupation	Student	77	35.0	35.0	35.0	2.43	1.231
	Private Job	33	15.0	15.0	50.0		
	Govt. Job	48	21.8	21.8	71.8		
	Others	62	28.2	28.2	100.0		
Familiar with the definition of Artificial Intelligence (AI)	Yes	168	76.4	76.4	76.4	1.39	.735
	No	19	8.6	8.6	85.0		
	Maybe	33	15.0	15.0	100.0		
Which MFS service do you use frequently?	Rocket	12	5.5	5.5	5.5	3.25	3.373
	bKash	169	76.8	76.8	82.3		
	MYCash	3	1.4	1.4	83.6		
	Islami Bank mCash	9	4.1	4.1	87.7		
	Upay	5	2.3	2.3	90.0		
	Nagad	22	10.0	10.0	100.0		
Do you think your MFS company uses AI to design the MFS products and services?	Yes	111	50.5	50.5	50.5	1.87	.933
	No	26	11.8	11.8	62.3		
	Maybe	83	37.7	37.7	100.0		

Source: Author's Survey Result

Table 3 illustrates the gender distribution of respondents, with just 43.2 percent identifying as male. Furthermore, the proportion of female respondents is 56.8 percent. The age distribution of the participants in the table encompasses the following ranges: The age ranges include 18-28, 29-39, 40-50, and over 51 years. It indicates that 74.5 percent of respondents are between 18 and 28 years old. Only 18.6% of the respondents are between 29 and 39 years old. Merely 6.8% of the respondents are between 40 and 50 years old. No respondents were identified in the remaining age categories. The participants' educational attainment is presented in the table. The distribution of responses is as follows: 7.3% hold H.S.C., 24.5% possess Hon's degrees (BS/BBA/BA), 61.4% have Master's degrees (MS/MBA/MA), and 6.8% are PhD holders. No respondents were identified from the remaining educational groups. The table includes the monthly personal income of members. The highest percentage of respondents, 47.7%, belong to the first income category, while 14.5% fall into

the second category. Additionally, 13.2% are classified in the last category, 10% in the fourth category, and 7.3% are represented in both the third and fifth categories simultaneously. The table includes the occupations of the participants. In this context, 35.0% are students, 15% are employed in the private sector, and 21.8% are government employees. Of job holders, 28.2% represent other job holders. The biggest percentage of respondents, 76.8%, frequently utilize the MFS (bKash) service. The lowest rate of respondents who usually use the MFS (MYCash) service is 1.8. Approximately 76.4% of respondents are familiar with the definition of artificial intelligence (AI). Only 8.6% of respondents are unfamiliar with the definition of artificial intelligence (AI), whereas 15% may have some familiarity with it. Ultimately, 50.5% of respondents believe that their MFS company employs AI in the design of MFS products and services. Only 11.8% of respondents believe that their MFS company uses AI in the design of MFS goods and services.

7.2 Descriptive Statistics Analysis

The succeeding table shows the descriptive statistics outcome; it showed that user-friendliness, personalization, trust, relationship commitment and user satisfaction are the five variables of users' perception factors. AI-driven user experience had two variables: AI-hedonic user experience and AI-recognition user experience. The researchers have constructed a scoring range of values to identify the most significant target variables. The study has shown a mean value between 3.41 and 4.20, that's why five variables are regarded as the target variables (Akter & Mia, 2023). Here, seven variables possess a mean value ranging from 3.1 to 4.0; hence, these variables are considered the consensus components for identifying the target users' perception factors.

Table 4: Descriptive Statistics of the Variables

Factors Name	N	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
UF	220	3.4500	1.04434	1.091	-.645	.164	-.074	.327
PER	220	3.4040	1.06493	1.134	-.578	.164	-.248	.327
TRU	220	3.3264	1.02509	1.051	-.661	.164	.009	.327
RC	220	3.3064	1.09984	1.210	-.447	.164	-.483	.327
US	220	3.3445	.93184	.868	-.634	.164	.295	.327
HUE	220	3.4400	1.06939	1.144	-.738	.164	.019	.327
RUE	220	3.3582	1.06092	1.126	-.595	.164	-.176	.327
Valid N (listwise)	220							

Source: Author's Survey Result

7.3 Reliability Analysis

It is necessary to have a reliability threshold of 0.7 or higher in order to proceed with the research. Cronbach's alpha is utilized to evaluate the internal consistency of questionnaires. According to the information shown in Table 5, Cronbach's alpha for the seven variables, which includes a total of 33 items (five items for each variable), is .975. It indicates that there is a high degree of internal

consistency among the items that were chosen. Additionally, as shown in Table 6, the Cronbach's alpha rating for every item is higher than 0.7. Every single item may be relied upon.

Table 5: Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.975	.975	33

Table 6: Summary of the Cronbach's Alpha Rating of the Items

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
UF1	107.75	846.086	.584	.975
UF2	107.75	846.086	.584	.975
UF3	107.87	849.823	.551	.975
UF4	107.89	847.248	.613	.975
UF5	107.89	847.248	.613	.975
PER1	107.79	843.000	.753	.974
PER2	107.79	843.000	.753	.974
PER3	108.12	841.392	.736	.974
TRU1	108.00	834.689	.742	.974
TRU2	108.00	834.689	.742	.974
TRU3	108.00	834.543	.803	.974
TRU4	108.01	846.361	.679	.974
TRU5	107.76	840.677	.753	.974
RC1	108.06	841.996	.613	.975
RC2	108.06	841.996	.613	.975
RC3	107.76	840.677	.753	.974
RC4	108.09	831.303	.796	.974
RC5	107.90	829.767	.816	.974
US1	108.00	838.863	.728	.974
US2	108.00	838.863	.728	.974
US3	107.84	845.443	.702	.974
US4	107.85	849.629	.639	.974
US5	108.01	846.361	.679	.974
HUE1	107.94	830.056	.836	.973
HUE2	107.82	838.971	.831	.974
HUE3	107.82	838.971	.831	.974

Items	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
HUE4	107.82	838.971	.831	.974
HUE5	107.81	836.810	.763	.974
RUE1	107.95	834.280	.828	.973
RUE2	107.95	834.280	.828	.973
RUE3	107.95	834.280	.828	.973
RUE4	107.95	842.837	.744	.974
RUE5	107.84	839.544	.763	.974

Source: Author's Survey Result

7.4 Hypothesis test Analysis

A summary of the hypothesis test among the variables' has been found in Table 7. The value of the first user perception component, which is referred to as User-friendliness (UF), is 640, which indicates that there is a moderately positive linear correlation with the AI-driven user experience (AI UE). In contrast, the value .616 demonstrates a moderately positive linear connection between AI recognition user experience (RUE) and the number.609 indicates that UF has a moderately positive linear correlation with AI-hedonic user experience (HUE). The value of .220 for the second user perception component, which is referred to as Personalization (PER), indicates that there is a positive linear link with AI-driven user experience (AI UE). A positive linear connection exists between PER and AI-hedonic user experience (HUE), as indicated by the value.209, while a positive linear correlation exists between PER and AI-recognition user experience (RUE), as highlighted by the value .232 in the Table 7. There is a strong positive linear link between the third user perception factor, Trust (TRU), and the AI-driven user experience (AI UE), as indicated by the user perception factor's value of .816.

While the value of.777 shows a strong positive linear relationship with AI recognition user experience (RUE), the value of.786 indicates that TRU has a strong positive linear relationship with AI-hedonic user experience (HUE). The value of the fourth user perception factor, Relationship Commitment (RC), is 794, which indicates that there is a significant positive linear correlation with AI-driven user experience (AI UE). A substantial positive linear correlation exists between RC and AI-hedonic user experience (HUE), as indicated by the value 778. On the other hand, the value.743 indicates a significant positive linear correlation between RC and AI-recognition user experience (RUE). There is a strong positive linear link between the fifth user perception factor, user satisfaction (US), and AI-driven user experience (AI UE), as indicated by the value of.821 for this factor. The value of 806 demonstrates a strong positive linear correlation between user satisfaction (US) and the AI-recognition user experience (RUE), while the value.766 indicates a robust positive linear correlation between user satisfaction (US) and the AI-hedonic user experience (HUE).

In the end, the significance of users' perception factors (UPF) indicates that there is a strong positive linear link between UPF and AI-driven user experience (AI UE). On the other hand, the value of.841 demonstrates a strong positive linear correlation between UPF and AI-recognition user experience

(RUE), while the value of .834 indicates a robust positive linear association between UPF and AI-hedonic user experience (HUE).

Table 7: Correlations among variables

Factors Name			HUE	RUE	AI_UE
UF	Pearson Correlation	1	.609**	.616**	.640**
PER	Pearson Correlation	1	.209**	.232**	.220**
TRU	Pearson Correlation	1	.786**	.777**	.816**
RC	Pearson Correlation	1	.778**	.743**	.794**
US	Pearson Correlation	1	.766**	.806**	.821**
UPF	Pearson Correlation	1	.834**	.841**	.874**
**. Correlation is significant at the 0.01 level (2-tailed).					

Source: Author's Survey Result

7.5 Regression Analysis

Model Estimation

In Table 7, personalization (PER) showed a positive but weaker relationship with AI_UE ($r = .220$). Strong correlations between other predictors and usage experience highlight the importance of these factors. PER had a weaker correlation and shared variance with stronger predictors, so it did not have a significant effect on the regression analysis. Although PER was positively related to AI usage experience in a simple analysis, it did not add unique value to the multiple regression model. PER overlapped with other predictors. Removing PER did not reduce the model's overall performance. Personalization (PER) was excluded from the regression model due to its non-significant effect. The revised regression model includes User Friendliness (UF), Trust (TRU), Relationship Commitment (RC), and User Satisfaction (US) as predictors of AI-driven User Experience (AI_UE), as presented below:

$$AI_UE = \text{Constant (D)} + \beta_1 UF + \beta_3 TRU + \beta_4 RC + \beta_5 US + \text{Error}(e_i)$$

Table 8: Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.881 ^a	.776	.772	.48716
a. Predictors: (Constant), US, UF, RC, TRU				

Source: Author's Survey Result

Here, the **R-value** is 0.881. It demonstrates a straightforward correlation, indicating a robust positive linear relationship between the correlated variables and the independent variables.

The R square **value** is .776. The value signifies the extent to which the dependent variable (AI-driven user experience) may be elucidated by the independent variables: user-friendliness (UF), trust (TRU), relationship commitment (RC), and user satisfaction (US). The independent variables explain 77.6 percent of the variance in AI-driven user experience. The total is substantial in percentage terms.

The **adjusted** value is 0.772, indicating that the inclusion of extra independent variables enhances the experience of AI-driven users. The modified value illustrates the impact of including supplementary independent factors on the dependent variable. Incorporating additional independent variables will improve the AI-driven user experience, provided that the adjustment is proximate to the optimal value.

Significance Testing

$H_0 : R_{pop}^2 = 0$ (There is no association between AI-driven User Experience with user-friendliness (UF), trust (TRU), relationship commitment (RC) and user satisfaction (US))

$H_1 : R_{pop}^2 \neq 0$ (There is a significant association between AI-driven User Experience with user-friendliness (UF), trust(TRU), relationship commitment(RC) and user satisfaction(US))

Table 9: ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	176.815	4	44.204	186.259	.000 ^b
	Residual	51.025	215	.237		
	Total	227.840	219			
a. Dependent Variable: AI_UE						
b. Predictors: (Constant), US, UF, RC, TRU						

Source: Author’s Survey Result

The aforementioned ANOVA table can be used to examine the hypotheses. In an analysis of variance (ANOVA) table, a 0.000 significant value rejects the null hypothesis. Accordingly, the researcher rejects the null hypothesis. Indeed, accepting the alternative hypothesis is necessary. The independent factors have a strong correlation with the AI-driven user experience.

Table 10: Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	
	B	Std. Error	Beta			
1	(Constant)	.084	.132		.634	.527
	UF	.133	.043	.136	3.090	.002
	TRU	.202	.068	.203	2.959	.003
	RC	.291	.049	.313	5.876	.000
	US	.366	.068	.334	5.414	.000
a. Dependent Variable: AI_UE						

Source: Author’s Survey Result

The total value of the Regression Model is given below:

$$\text{AI-driven User Experience} = .084 + .133(\text{user-friendliness}) + .202(\text{trust}) + .291(\text{relationship commitment}) + .366(\text{user satisfaction}) = 1.076$$

The AI-driven user experience's overall score of 1.076 indicates that the dependent variable is positive. Additionally, this model demonstrates that users' perceptions are an important criterion for obtaining a completely positive rating for the AI-driven user experience. The unstandardized coefficient value for UF (0.133) indicates that the MFS firms provide each additional user-friendly service to the virtual app users. Thus, the AI-driven user experience is expected to increase by 0.133 points. TRU (0.202) indicates that each additional user trust, e.g., increases app security, and the MFS firms provide reliability, etc., to the virtual app users.

Thus, the AI-driven user experience is expected to increase by only 0.202 points. RC (0.291) indicates that each additional relationship commitment, e.g., emotional and personal attachment, recognized with MFS firm etc., increases, thus the AI-driven user experience is expected to increase by only 0.291 points. US (0.366) indicates that each additional user satisfaction, e.g., quality of service, focus on customer interest, etc. increases. Thus, the AI-driven user experience is expected to increase by only 0.366 points.

Table 11: Summary of the Hypotheses Testing Result

Factors Name	Hypothesis No.	t value	P value	Decision
User Friendliness (UF)	H1	12.288	.000	significant
	H1a	11.328	.000	significant
	H1b	11.560	.000	significant
Personalization (PER)	H2	3.497	.001	significant
	H2a	3.156	.002	significant
	H2b	3.529	.001	significant
Trust (TRU)	H3	20.828	.000	significant
	H3a	18.759	.000	significant
	H3b	18.201	.000	significant
Relationship Commitment (RC)	H4	19.299	.000	significant
	H4a	18.281	.000	significant
	H4b	16.390	.000	significant
User Satisfaction (US)	H5	21.208	.000	significant
	H5a	17.604	.000	significant
	H5b	20.088	.000	significant
User Perception Factors (UPF)	H6	26.620	.000	significant
	H6a	22.283	.000	significant

Factors Name	Hypothesis No.	t value	P value	Decision
	H6b	22.972	.000	significant

Source: Author's Survey Result

Table 11 shows that Hypothesis H1 and its sub-hypotheses (H1a and H1b) are supported with high t-values (11.328 to 12.288) and p-values below .001. This shows how easy it is to use and how clear the interface is, which has a big effect on the outcome variable, indicating how important these factors are in getting people to respond. Hypothesis H2 and its associated sub-hypotheses (H2a, H2b) have statistical significance ($p \leq .002$). The findings indicate a favourable correlation between personalization and the dependent variable. However, the regression analysis shows that this effect is not significant when other variables are taken into consideration. This suggests that there is shared variance with more important predictors. Hypothesis H3, which includes H3a and H3b, has strong statistical support, as shown by t-values above 18 and p-values below .001. This research underscores trust as a critical factor and highlights its influence on user outcomes Hypothesis H4 and its sub-hypotheses (H4a, H4b) are significantly supported ($p < .001$). The high t-values indicate that relationship commitment is an important predictor of the dependent variable. This shows how important relational elements are in the study framework. There is very strong statistical evidence ($p < .001$) that supports hypotheses H5, H5a, and H5b. This indicates that content users are significantly more likely to report favourable outcomes, consistent with accepted theories of post-adoption and user experience. Finally, Hypothesis H6 and its sub-hypotheses (H6a, H6b) have the greatest t-values in the table, all of which are significant at $p < .001$. This means that the overall user-perception components are strongly linked to the dependent variable, indicating their importance in shaping user ratings.

8. Discussion on the findings

The above analysis shows that MFS companies should focus on the five users' perception factors to boost AI-driven user experience. The study showed how the respondents are linked to many socio-economic factors. The descriptive Statistics showed that the five factors under users' perception factors, named user-friendliness, personalization, trust, relationship commitment and user satisfaction and also the two factors under AI-driven user experience, named AI-hedonic user experience and AI-recognition user experience, have a mean value of between 3.1 to 4.0 Which indicates all the respondents agree with the items that selected for all the factors. The practicality of the findings in the MFS sector will rely on the user's degree of knowledge and experience. This paper identifies users of a virtual/mobile application inside a mobile financial service sector as having exceeded factors. MFSs must reach user preferences and demands by data analysis if they are to offer tailored services and instantly answer user questions.

This study examined user perceptions of AI usage in mobile financial services with a modified multiple regression model. The findings indicate that user-friendliness, trust, relationship commitment, and user satisfaction have a substantial and favorable impact on AI_UE; however, Personalization does not show a substantial independent impact. The updated model accounts for a significant portion of the variance in AI usage experience, validating its considerable explanatory power and reliability. All the hypotheses aligned with the previous study of Tulcanaza-Prieto et al. (2023), which means the results can be trusted. Their analysis revealed that all five customer

perception factors positively and significantly affect AI-enabled customer experience, hedonic customer experience, and recognition of customer service. The results also aligned with earlier studies and showed how users view the tangible and intangible advantages of AI-driven banking capabilities, as well as the digital infrastructure supplied by banks, define AI-driven financial services. Research conducted in many Asian countries, European cities, India, the UK, Canada, Nigeria, and Vietnam has shown a strong association between AI-driven user experience and consumer perception aspects. Furthermore, AI techniques can improve user perception factors (Noreen et al., 2023; Chen et al., 2023; Mogaji & Nguyen, 2022; Cheriyan et al., 2022; Ameen et al., 2021; Juwaheer et al., 2012). Furthermore, there have not been any similar studies done in Bangladesh, so it is not possible to compare results.

The presumptions of this study were mostly accurate as users' opinions of their experiences could alter the pursuit usage of AI-driven mobile financial services. The more the virtual app of MFS firms is personalized, the MFS products and services (e.g., fund transfer, cash-in and out, pay bill) are designed in accordance with users consumption preferences, chatbot and self-help customer service are provided solutions as per users expectations, the virtual app is adjusted itself according to the device users used, the more the users may rely on the virtual app for fulfillment their needs. Therefore, experienced users aided by AI are more influenced in the direction of MFS enterprises. Users should be more sensitive and conscious; the AI-assisted and AI-driven experience could be improved. An AI-driven user experience that meets user expectations helps to become more competitive than rivals. The MFS sector must thus evaluate users' data privacy and security, provide relevant variables to AI training models, and offer a user-friendly chat interface or virtual platform to ensure that mobile financial services are easy to use and safe for users. Moreover, there is little difference if related studies are conducted. Businesses in the mobile financial services sector can get a boost in terms of investing in and applying artificial intelligence to their banking operations with the fresh knowledge acquired from this study. A better user experience with these services will captivate users.

9. Conclusions

This paper evaluates the beneficial influence of the factors influencing user perception on AI-driven user experience by means of a thorough and strong statistical model. This paper delves into a topic that has not received much attention in the local context: it presents theoretical and empirical data on the correlation between user perception factors and AI-driven user experience for Mobile Financial Services (MFS) in Bangladesh. This paper emphasized the importance of incorporating AI into the design of financial products and services, utilizing consumer preferences and purchase behavior as primary sources of information to gain sustainable competitive advantage. Modern technology and strategies combined with an integrated representation of the customer perspective help to develop the AI-driven customer experience. This strategy shows how users perceive AI capabilities, therefore fostering a user-centric viewpoint on the technology. Users may raise their standards for goods and services, which could make the market more competitive and lead to a constant rise in customer needs and wants. It could be helped by using AI techniques. As such, AI virtual/mobile apps must ensure confidentiality, privacy, and data integrity are guaranteed.

Furthermore, AI systems incorporate decision-making and evaluation procedures, which could replace human approaches. Ethics training for AI professionals must be included in current laws, societal conventions, and ethical standards in order to match. AI's research and implementation

must be guided by established regulatory frameworks that also provide direction to the government and encourage public debate, thus defining ideas.

10. Future Scope of Research

Research on the factors that users believe affect the quality of AI-driven mobile financial service (MFS) user experiences in Bangladesh has a wide range of potential avenues to explore in the future. The rapid growth of mobile financial services in Bangladesh is driven by factors such as the increasing number of people using smartphones and mobile internet, together with the introduction of AI technologies that enhance the user experience. If researchers want to get a better picture of the population at large, they should consider using stratified or random sampling in their future studies. Moreover, applying multivariate statistical methods will help to improve understanding and enable the control of confusing elements. Additionally, the study examines direct effects only; future research could explore mediating or moderating roles of personalization, trust, or satisfaction. For more research, it would be helpful to have a sample that is more representative of the larger Bangladeshi MFS user community and shows the range of geography and financial knowledge. Further research suggests how technological understanding of AI affects users' opinions and experiences with AI-driven items. How much does users' understanding of AI ideas impact their adoption and trust in AI systems? Also, how can AI systems meet the unique needs of different domains while ensuring the best possible user experience? When trying to influence users' perceptions of AI, what domain-specific challenges arise, and how may they be addressed through design?

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