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Investigating continuance intention to use m-banking apps among older adults using partial least squares modeling with income group differences

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Abstract

Information technology accelerates global economic development and enhances quality of life, playing a pivotal role in advancing the United Nations Sustainable Development Goals (SDGs). In particular, mobile banking applications (m-banking apps) contribute to digital financial inclusion, which is central to achieving SDG 1 (No Poverty), SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation and Infrastructure), and SDG 10 (Reduced Inequalities). Despite these potential benefits, sustained usage of m-banking services among vulnerable populations such as older adults remains limited, thereby constraining long-term developmental impact. Recognizing this gap, the current research investigates the antecedents influencing the continuance intention to use m-banking apps in the Bangladeshi context, focusing on older adults with prior usage experience. Utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) with a final valid sample of 160 older adults (aged 60 years and above) residing in the Dhaka metropolitan area of Bangladesh, the analysis adopts an integrated framework combining elements from the Information Systems success model, Expectation Confirmation Model, and Unified Theory of Acceptance and Use of Technology, while incorporating trust and perceived risk. Additionally, income-based multi-group analysis is conducted to capture heterogeneity in digital financial inclusion outcomes. The empirical findings reveal that system quality, trust, and perceived risk significantly influence confirmation of m-banking usage. Multigroup analysis further indicates that information quality, system quality, and service quality differ significantly between lower- and higher-income groups, highlighting inequality in digital service experiences. By identifying the drivers of sustained m-banking usage among older adults, this study contributes to the sustainable development agenda by demonstrating how improving system quality, trust, and risk perceptions can enhance long-term digital financial inclusion. The findings offer actionable insights for financial institutions and policymakers aiming to design inclusive digital services



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that support equitable economic participation and advance progress toward the SDGs.

Keywords Continuance intention, m-banking apps, Older adults, IS success, ECM, UTAUT

1 Introduction

Technological advancements, high-speed internet connectivity, and the ever-growing smartphone market enable financial institutions to provide an extensive range of integrated banking services. Additionally, conventional transaction systems have been supplanted by m-banking, which has played a breakthrough role in out-of-the-way banking services [78, 101]. M-banking utilizes the technological advancement of mobile phones to accomplish financial transactions [84, 123]. In-depth, an m-banking app can be delineated as a software application that clients of financial institutions download on their mobile device that facilitates performing, not limited to, transferring money, checking accounts, making payments, finding ATM's locations, receiving alerts for financial services, investing in stock market, checking personal financial information, saving beneficiary information, requesting accounts statement, and so on [11, 56, 77]. Consequently, customers use their smartphones and tablets to conduct nearly all types of banking services pervasively [40, 57, 149]. Hence, Bill Gates anticipates that by 2030, there will be more than 2 billion subscribers to m-banking apps [122]. Additionally, during COVID-19, m-banking app usage was accelerated to avoid virus transmission, and consumers frequently transacted financial deals and paid electricity as well as utility bills [115].

In this digital era, mobile applications are very familiar to smartphone users [71], and among them, m-banking apps are highly technologically advanced, innovative, and versatile. Consumers get profuse benefits and lucrative opportunities from the usage of m-banking apps to execute their daily financial activities [6, 86]. Clients can save their valuable time and money as m-banking apps facilitate tremendous benefits like convenience, ease of use, low financial fees [45, 46, 85], privacy maintenance, security, flexibility [77], customized services, high interaction, and so on [45, 46]. Therefore, undoubtedly, individuals' quality of life improved more than ever before [92, 135]. Moreover, ample financial rewards are reaped by financial institutions through utilizing m-banking apps services, such as cost reduction [129], lowering operating costs, productivity improvement, decreasing the number of branches [130], understanding clients behaviour pattern, enlarging clients base, and maximizing revenue [70, 126].

Although m-banking apps offer numerous benefits, there are also complaints about them. Clients frequently complain about m-banking apps being dysfunctional, challenging to understand, and confusing. Moreover, the majority of complaints faced by clients can be categorized into security, usability, and convenience. Therefore, managers should be concerned and learn to solve these complaints as financial payoffs are associated with m-banking services [122]. Also, another study reported that the banking sector has struggled with several issues pertinent to m-banking apps, which are security, high-tech product requirements, technological infrastructure, and user training [133].

Most of the prior literature has examined m-banking services adoption [9, 12, 36, 83, 108], digital banking adoption of non-users [128], mobile banking service continuation intention [40, 68, 89, 90, 111, 135] and m-banking apps acceptance [6, 7, 75, 95, 124, 146]. Nevertheless, few investigations have focused on the precursors of m-banking

apps' continuance usage intention [82, 112]. In addition, in the context of Bangladesh, studies concerning m-banking app continuation willingness have not yet been conducted, thus, the study contributes to the existing knowledge domain as well as aids the practitioners of financial institutions. What's more, this research specifically focuses on older adults aged more than sixty years, as the aging population is increasing fast. Worldwide, around 1 billion people were older adults in 2020, and by 2030, this figure will become 1.4 billion. Furthermore, nearly 80 percent of ageing people worldwide will be living in developing and underdeveloped countries by 2050. Hence, these older adults gradually reduce physical mobility and require special care. However, they still contribute in several ways to the economy and society if opportunities are provided [155].

Hence, the m-banking app is a blessing for them as it facilitates remote banking services. Society as a whole needs to pay attention to them and develop strategies that will be more amicable to the ageing population. Consequently, this study provides several insights to policymakers and assists in designing ageing people-friendly m-banking apps that, in turn, influence the willingness to continue. Therefore, the current study will be addressing the following research questions:

- What factors significantly influence the intention of older adults in Bangladesh to continue using m-banking apps?
- Are there any differences between lower-earners and higher-earners among older adults in confirming the usage of m-banking apps?

Abundant m-banking services are accessed through several ways, which are mainly categorized into three channels, such as short message services, mobile internet, and downloadable m-apps, and among these m-apps are enormously popular [131, 132]. Hence, the study endeavours to focus only on downloadable m-banking apps' continuance usage intention. To attain the aforementioned goal, the study developed a research model that combined the IS (Information System) success model, the ECM (Expectation Confirmation Model), and the UTAUT model.

Bangladesh witnesses the fastest-growing economy and is pursuing becoming an upper-middle-income country by 2031 [145]. As a developing country, it has transitioned from an underbanked community to a modern digital banking services society. Financial inclusion deepens the country's economy, and the m-banking app assists in including more people who were previously financially excluded.

Mobile application usage has been seen very often among smartphone users [134]. In 2022, the smartphone penetration rate in Bangladesh was nearly 47 percent, and the Global System for Mobiles (GSM) Association anticipates that by 2025, this penetration rate will increase to 63 percent [100]. Also, the Bangladesh Bureau of Statistics (BBS) reported that in 2022, for people more than 15 years old, mobile phone usage accounted for 73.8 percent, and the internet usage rate was 45.5 percent. [140]. According to the Association of Mobile Telecom Operators of Bangladesh (AMTOB), the number of mobile phone subscribers peaked at 189.67 million in October 2023 [69].

In 2019, there were approximately 2.05 million m-banking app users, which tripled within three years and reached around 6.6 million in 2023. The Bangladesh Bank, which is the central bank, reported that among the several mobile banking apps, the most renowned are "Nexus Pay", "Cellfin", "Astha", "eSheba", "Sky EBL", and "City Touch". Nearly 66 percent of mobile-based transaction clients are from Nexus Pay and Cellfin. In

Bangladesh, apart from banks, mobile financial institutions (MFS) also use mobile apps, such as bKash, Rocket, Nagad, and Upay. The total volume of app-based transactions was BDT 293.86 billion in February 2023, as reported by Bangladesh Bank [35].

The remaining sections of the study are structured as follows: Sect. 2 discusses the literature review, while Sect. 3 presents the research methodology. Subsequently, empirical results are portrayed in Sect. 4. The discussion and implications of the study are presented in Sect. 5, followed by Sect. 6, which addresses the limitations and future research directions. Finally, Sect. 7 concludes the study.

2 Literature review and research model

Technology advancement has transformed financial services significantly in the last decades [93]. A conspicuous change has been seen in clients' usage of financial services, shifting from traditional banking to online banking, especially m-banking services. Additionally, several established theories were explored for scrutinizing the adoption intention as well as the continuation willingness of clients towards m-banking services [13, 24, 146].

The information technology adoption issue, which is a one-shot activity, is quite different from the intention to continue using IS [59]. The sustainability of any kind of IT depends on the users' continued willingness to use it. Therefore, the sustainability of IT is significantly related to continuance intention, and regarding this aspect, the expectation confirmation theory is prominent [19]. This theory has proved that consumers' satisfaction with IT is captured by the degree to which the consumers' initial expectations of IT have been met while using that IT [19, 20]. Zhou [157], Hidayat-ur-Rehman et al. [64], and Seethamraju et al. [125] integrated the ECM and UTAUT models in different contexts. Cheng [28] combined the ECM model, IS model, and flow theory to examine nurses' continued intention for blended e-learning. Nevertheless, the UTAUT model, formulated by Venkatesh et al. [150], stands as the most extensively employed theory among information systems researchers.

Susanto et al. [141] suggested a model by extending ECM theory to identify the factors of continuance willingness for smartphone mobile banking services in Korea. Moreover, Yuan et al. [156] integrated several models, such as TAM, TTF, and ECM models, with perceived risk (PR) in the context of China for clients' intention to continue using m-banking services. Several studies have implemented ECM as an underpinning theory to assess users' continuation intention for information technology [30, 47, 103]. Thus, ECM has more predictive capability for continuance willingness of any kind of IT.

Zhou [158] combined the IS success model and flow theory to inspect the mobile payment continuation intention of end users. Moreover, Zhou suggested that to encourage users' continued usage of the m-payment system, service providers should concentrate on offering improved systems, quality information, and services. In another study, Zhou et al. [159] examined m-banking adoption intention by combining the TTF (Technology Task Fit) and UTAUT models.

However, in developing countries like Bangladesh, no significant studies have been conducted to identify factors of continuation usage intention of users for m-banking applications. Moreover, the present study concentrates on the segment of the elderly population of Bangladesh, which has also not yet been addressed by other research endeavours. Therefore, the study amalgamates the UTAUT Model, IS success model,

and ECM Model to accomplish research objectives. These three models were selected over alternative frameworks, such as the Technology Acceptance Model (TAM) or Task-Technology Fit (TTF), based on theoretical fit and empirical precedent. The IS success model [34] is uniquely suited to capture multi-dimensional quality assessments (information, system, and service quality) that are central to evaluating post-adoption experiences. The ECM [19] is the dominant framework for continuance intention research, as it specifically models how prior usage experience shapes expectations, confirmation, and satisfaction—a logic absent from adoption-focused models like TAM or TTF. UTAUT [150] extends the ECM by incorporating social and motivational antecedents (effort expectancy, performance expectancy, and social influence that are especially relevant for older adult populations who may rely on external encouragement to persist with digital financial tools. TAM was excluded because it does not account for post-adoption dynamics or quality dimensions, TTF was excluded because it focuses on task-technology alignment at the adoption stage, not continuance. Trust and perceived risk were additionally incorporated due to their contextual fitness for this demographic and setting. In particular, older adults face augmented digital financial risks that younger users are less susceptible to: they are disproportionately targeted by online fraud and phishing attacks [10], often lack the digital literacy to recognize security threats, and tend to suffer greater financial and emotional harm when fraud occurs due to limited recovery resources. The fear of losing hard-earned savings through a digital transaction, the anxiety of unknowingly sharing credentials, and the distrust of unfamiliar digital interfaces collectively constitute a unique risk landscape for elderly m-banking users. These concerns are further compounded in the Bangladeshi context, where consumer protection mechanisms and digital grievance redressal systems remain nascent. Accordingly, trust and perceived risk are theoretically indispensable for understanding whether older adults in this setting feel that m-banking apps have fulfilled or failed to fulfill their basic expectations of safety and reliability. The following sections will explicate the conceptual framework and hypothesis of this study.

2.1 Theoretical framework and hypothesis development

Based on the extent of the literature, the study proposes a research model in which information quality, system quality, and service quality have been adapted from the IS success model [34]. Moreover, from the widely used UTAUT model, the effort expectancy, performance expectancy, and social influence constructs have been extracted [150]. Besides, from the ECM model, vital constructs, such as satisfaction, confirmation, and continued usage intention, have also been implemented. Finally, two additional variables, such as trust and PR, were incorporated due to contextual fitness, which was also derived from prior literature [64, 73, 112, 133].

2.2 Information quality (IQ)

Only information systems performance is not sufficient to satisfy users. Instead, the produced information quality is also a crucial factor. The output of the system should be reliable, accurate, timely, relevant, complete, and precise [33]. Information users become dissatisfied when they get low-quality information from the system [104]. Prior literature revealed that information quality is an influential driver of user satisfaction [58] and thereby confirmation [42, 43, 79]. Thus, the subsequent hypothesis was proposed:

H1 *Information quality of mobile banking apps positively impacts the older adult's extent of confirmation of expectation.*

2.3 System quality (SYQ)

System quality encompasses reliability, flexibility, user-friendliness, responsiveness, and quality output of an information system usage [34]. As users' satisfaction regarding handheld wireless devices is strongly related to system quality, the continuance intention for mobile-based app services is likewise impacted by system quality [21]. The intention to adopt e-learning among learners and instructors is determined by system quality [105]. Furthermore, Aldholay et al. [5] demonstrated that system quality positively affected the satisfaction of e-learning users, while Chang et al. [23] found that system quality influences satisfaction with digital banking. Teo et al. [144] asserted that system quality is the main predictor of confirmation of technology usage, which in turn influences users' satisfaction. Thus, the following statement is hypothesized for this research:

H2 *System quality of mobile banking apps positively impacts the older adult's extent of confirmation of expectation.*

2.4 Service quality (SQ)

Delone and McLean [34] outlined the term service quality as the degree to which information systems users appraise services as well as follow-up facilities. Regarding the e-commerce sector, Liu and Arnett [91] referred to service quality as swift responsiveness, commitment, and follow-up services. Moreover, they emphasized that an e-commerce website's success greatly depends on its service quality. Besides, e-health service providers also emphasize service quality to ensure the satisfaction and retention of users [102]. Consequently, continuation intention, satisfaction, and confirmation have a strong positive association with the overall quality of information systems [3, 58]. This study devises the subsequent hypothesis:

H3 *The service quality of mobile banking apps positively impacts older adults' level of confirmation of expectation.*

2.5 Effort expectancy (EE)

The term "effort expectancy" signifies the degree of user-friendliness of newly introduced information technology [151]. Saparudin et al. [123] demonstrated that the inclination to continue using m-banking services is significantly and positively influenced by effort expectancy. Again, Huang and Kao [66] found effort expectancy to be a prominent yardstick for acceptance of information technology. In the post-adoption stage, the effort expectancy constructs also positively dominate the confirmation usage of m-banking services, as established by Hidayat-ur-Rehman et al. [64]. Further, prior literature results showed that when clients' experience is far better than their perceived beliefs towards user-friendliness and effort requirement to operate the system, their intent to persist in m-banking services is reinforced [139, 146, 156]. Therefore, the next hypothesis is designed:

H4 *Effort expectancy of m-banking apps positively impacts the older adult's extent of confirmation of expectation.*

2.6 Performance expectancy (PE)

Venkatesh et al. [150] demarcated performance expectancy as the extent of users' perception of improving their job tasks using a system. When IS users get their desired benefit, they become satisfied [19]. Saparudin et al. [123] used criteria such as usefulness, comparative advantage, job fitness, expectation of benefit, and improved services. They revealed performance expectancy as a strong driver that positively influenced clients for the continuance of m-banking services. In addition, Kaium et al. [74] also discovered that performance expectancy was the most potent predictor of continuance intention of m-health services. They affirmed that users who frequently used m-health services had more expectations that innovative technology in healthcare services would benefit them. Hence, the subsequent assumption is suggested for this study:

H5 *Performance expectancy of mobile banking apps positively impacts the older adult's extent of confirmation of expectation.*

2.7 Social influence (SI)

Social influence refers to the impact of society members on the individual to adopt new innovative information technology. [150]. Abundant previous studies have indicated that social influence (SI) has a positive effect on the adoption of mobile banking services [14, 93]. Moreover, users' enduring behavioral intention for mobile banking services is also positively affected by the SI factor established in earlier research [123, 142]. However, in their study, Hidayat-ur-Rehman et al. [64] presented contrasting findings, where SI has a non-significant influence on satisfaction and the intention to continue using m-banking. Consequently, the ensuing hypothesis is proposed:

H6 *Social influence of mobile banking apps positively impacts the older adult's extent of confirmation of expectation.*

2.8 Trust (TR)

Trust is a crucial success factor in online business and transactions [67, 116]. Numerous previous research endeavors demonstrated that the trust factor strongly influences technology adoption [120], particularly continuance willingness of technology [42, 43, 133, 152] for m-banking services and the reason behind these findings was when users had trust in banking institutions and their activities then users will more satisfied and intended continued m-banking services. Furthermore, Shaikh et al. [127] examined continuance usage intention for m-banking services and identified trust [65] as one of the vital factors. Therefore, the following statement is assumed by us:

H7 *Trust of mobile banking apps positively impacts the older adult's extent of confirmation of expectation.*

2.9 Perceived risk (PR)

Featherman and Pavlou [37] demarcated PR as an individual's skeptical attitude toward the adverse consequences of using a service. In China, a study by Yuan et al. [156] showed that PR strongly negatively affected the intention to continue m-banking services. They suggested that banking service providers ensure adequate security for IT and offer guarantee statements and a helpline. Another study's output showed insignificant but direct impacts of perceived risk issues on continuance behavioral intention [88]. If end users feel a high perceived risk when adopting, purchasing, or continuing any information technology, they become reluctant to use that IT [42, 43, 73, 120]. However, Chen [26] explained a surprising outcome where perceived risk did not have significantly positive influence on the quality of the m-banking services. This result was also reinforced by Kang et al. [76], who revealed no significant effect of PR on m-banking perceived value. Thus, from the above literature findings, the hypothesis is generated and presented in the following:

H8 *Perceived risk of mobile banking apps negatively impacts the older adult's extent of confirmation of expectation.*

2.10 Confirmation (CON), satisfaction (STF), continuance usage intention (COUI)

Customers' satisfaction depends on the initial expectation fulfillment and their initial expectation arises from previous use, word of mouth and so on [112]. Abundant research works have shown that confirmation of expectation leads to customers' satisfaction, which in turn develops long-term good relationships with banking institutions [137, 141, 156]. Likewise, studies conducted in other domains, such as m-health [74], and transportation [27, 41], demonstrated confirmation that expectations generate satisfaction among users. After studying the above literature, the succeeding assertion is hypothesized:

H9 *Confirmation of expectation positively impacts the older adult's satisfaction with mobile banking app usage.*

Fornell [38] stated that satisfaction can be defined as customers' subsequent appraisal of a company's services. Extant literature results exhibited a positive impact of satisfaction on the persistent behavioral intent of IS users [2, 106]. In the m-banking arena, clients' continuation willingness depends on the satisfaction level, if clients are pleased, they are more interested in persisting with m-banking services, as established by several studies [40, 64, 112, 138, 156]. So, this research posits the following hypothesis:

H10 *Satisfaction positively impacts older adults' continued intention to use mobile banking apps.*

2.11 Income differences

Numerous studies have been conducted and discovered that different socio-demographic factors such as age [98], education [143], gender [147], and income level [63] have played a significant role in the adoption of m-banking services. Merhi et al. [96] investigated the moderating role of respondents' age and gender on the usage of mobile banking. Their findings showed that age and gender have a moderating effect on the

m-banking usage by Lebanese citizens. Clients with lower income are concerned about the financial cost associated with using m-banking services [32]. This study administered a multi-group analysis between lower earners and higher earners of elderly people to confirm the usage of m-banking apps, which was not explored by any previous literature. Therefore, the study proposed the following hypothesis: The strength of the association between Information Quality, Systems Quality, Service Quality, Effort Expectancy, Performance Expectancy, Social Influence, Trust, and Perceived Risk with the confirmation of m-banking apps usage will differ between low-income and high-income groups.

The following Fig. 1 depicts the research model that contains the respective hypotheses of this study.

3 Research methodology

3.1 Questionnaire design and development

The self-administered questionnaire of the study was designed after a rigorous review of prior research works. Additionally, as a research instrument, a survey was adopted. The initially developed questionnaire was assessed by three academicians with expertise in pertinent fields. Expert opinions were incorporated to ensure better understanding, clarity, and reliability. Then, the fine-tuned questionnaire was distributed among 35 pre-tested selected responders for performing pilot testing. Based on the insight of the pilot testing, some elements were added and redesigned to ameliorate the study. These pre-tested participants' responses were eliminated from the final data analysis of the survey.

People aged sixty and above were treated as older, whereas those aged fifty and above were considered pre-older in a study carried out by Salihu et al. [121]. The 60-year age threshold is further supported by the World Health Organization [155], which designates individuals aged 60 and above as older adults in developing country contexts,

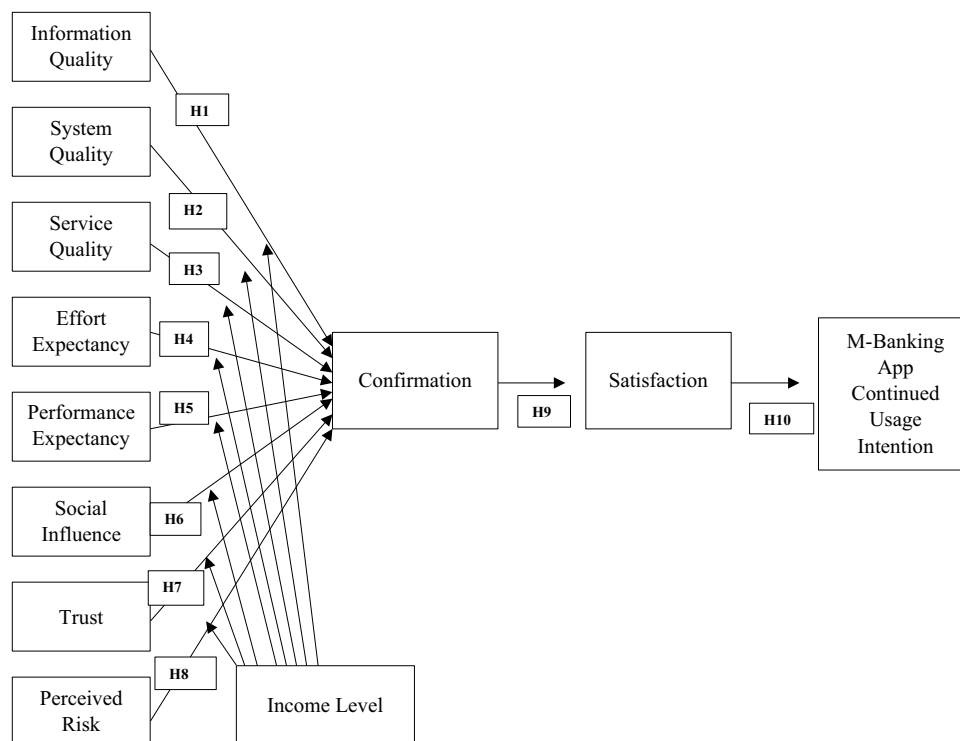


Fig. 1 Research model

and by the Bangladesh National Policy for Older Persons (2013), which identifies the 60+ age group as the primary target for elderly welfare interventions. Additionally, the Bangladesh Bureau of Statistics (2022) reports that the population aged 60 and above constitutes approximately 9% of Bangladesh's total population, a figure projected to rise significantly by 2030. Prior research in the Bangladeshi context, including Jafrin et al. [71], adopted the 60-year threshold in a closely related study on mHealth adoption by older adults. Therefore, bank clients aged sixty or above and those with banking app usage experience were the intended respondents of the study. Moreover, the Dhaka metropolitan city area was considered for data collection because: (1) it is one of the most densely populated cities with 43,500 people per square kilometre, (2) Dhaka accounts for the largest concentration of formally banked individuals and registered m-banking app users in Bangladesh [16] and (3) the city provides the highest density of elderly residents with prior mobile phone and m-banking exposure, making it the most appropriate setting for studying this population. Surprisingly, nearly 32 percent of the country's total urban dweller population lives in this city (Prothom [114]). This area was also chosen due to cost and time effectiveness. It is acknowledged that these findings may not be directly generalizable to rural areas or other divisions of Bangladesh, and future research should address this geographical limitation.

The questionnaire comprised two segments, namely, the respondents' demographic information and the intention to continue using the m-banking app. Respondents were requested to rate several statements regarding their willingness to continue. For the rating purpose, a Likert 5-point scale was adopted where "strongly disagree" and "strongly agree" were denoted by 1 and 5, respectively.

3.2 Sampling method and size

An appropriate sampling method and framework are essential to confirm a bias-free study. Since the population frame of older m-banking app users was unavailable in Bangladesh, a purposive (non-probability) sampling technique was adopted as the primary sampling strategy. Respondents were identified based on two eligibility thresholds: age of sixty years or above, and prior m-banking app usage experience. This deliberate screening ensured that only individuals with relevant usage experience were included, making purposive sampling the most appropriate approach for this study. Resource and time constraints further supported this decision.

The sample size was determined using G*Power software with configuration like effect size $f^2 = 0.15$, α err prob = 0.05, power ($1 - \beta$ err prob) = 0.95, and the number of predictors = 08 [71]. The software output suggested a minimum sample size of 160, which was adopted for this research. The sample size was further validated against PLS-SEM requirements. Following Hair et al. [48], PLS-SEM requires a minimum of ten times the maximum number of structural paths directed at any latent variable. In this model, a maximum of 8 paths point to the Confirmation construct, indicating a minimum sample of 80. The final sample of 160 comfortably exceeds this threshold. Furthermore, the inverse square root method [81] also confirms the adequacy of this sample size for the proposed model.

3.3 Data collection

The updated final questionnaire was disseminated to the target responders through online and offline channels. For offline data collection, trained data collectors conducted face-to-face surveys at bank branches, community centres, and senior citizen clubs in the Dhaka metropolitan area. For participants who faced vision difficulties or digital literacy challenges, data collectors read out each question and recorded responses on their behalf, ensuring that no respondent was excluded due to physical limitations. For online channels, Google Forms and e-mail were utilized; elderly respondents who required assistance were supported by a trained data collector, bank staff, or a trusted family member in completing the online questionnaire. Data collectors were trained to avoid leading respondents and to maintain neutrality throughout the process. Follow-up visits and telephone calls were made to ensure the completeness of submitted forms. Approximately 250 survey questionnaires, both online and offline, were circulated to ensure a high response rate. From the disseminated questionnaires, 182 responders returned their survey forms (return rate: 72.8%). However, 160 questionnaires were included finally for the data analysis as the remaining 22 had incomplete or unusable data, yielding an effective response rate of 64%. This response rate is considered acceptable for social science research [17] and is comparable to similar m-banking continuance studies. The data collection period was around four months, starting from June 2024 and ending in September 2024. Three data collectors were assigned for this purpose. With respect to ethical considerations, all participants were fully briefed on the research objectives and the voluntary nature of participation prior to data collection, and informed consent was obtained from each respondent. Respondent anonymity and data confidentiality were strictly maintained so that no personally identifiable information was collected or stored. The study was conducted in conformity with the ethical guidelines of the authors' home institution. Particular care was taken to minimize the physical and cognitive burden on older adult participants, given their age-related vulnerabilities.

3.4 Variable measurements

3.4.1 Information quality

Elements of information quality are adapted from prior studies [34, 107, 148], and these are (1) The information provided by m-banking apps is correct, (2) M-banking apps provide the information I need; and (3) I rely on the information generated by m-banking apps.

3.4.2 System quality

System quality construct encompasses the following items: (1) M-banking apps are user-friendly; (2) I can interact with m-banking apps anytime I want; and (3) M-banking apps make financial information easy to access [34, 99, 107, 148, 154].

3.4.3 Service quality

The items that comprise the service quality construct are as follows: (1) M-banking apps provide proper online assistance and explanation; (2) The service provided by m-banking apps fulfills my needs; (3) The service provided by m-banking apps can quickly respond to my needs [34, 99, 107, 148].

3.4.4 Effort expectancy

The three indicators of this variable are derived from previous research [136, 151] and revised due to contextual fitness. The adapted items are: (1) Understanding how to operate m-banking apps would be uncomplicated for me; (2) Interaction with m-banking apps would be obvious and comprehensible; and (3) I would find m-banking apps effortless.

3.4.5 Performance expectancy

After analyzing the literature, the ensuing items are acclimated for measuring performance expectancy: (1) M-banking apps are valuable in my day-to-day life activities; (2) Utilizing m-banking apps would assist me in conducting my economic activities more swiftly, and (3) Utilizing m-banking apps might support me to manage my financial planning [136, 151].

3.4.6 Social influence

The variable SI includes these elements: (1) Individuals who are vital to me believe that I should utilize m-banking apps; (2) Individuals who impact my behavior believe that I should utilize m-banking apps; and (3) Individuals whose thoughts I appreciate prefer that I use m-banking apps [136, 151].

3.4.7 Trust

Trust variable is conceptualized from different studies [123, 136] and measured by these statements: (1) I trust m-banking apps to be reliable, (2) I trust m-banking apps to be safe; and (3) I believe m-banking apps are trustworthy.

3.4.8 Perceived risk

Three indicators are adapted from literature to measure perceived risk construct, and these are: (1) I think m-banking apps are risky and dangerous to utilize; (2) Substantial threat involved in utilizing m-banking apps rather than other means of banking services (e.g., traditional banking); and (3) Overall, regarding all aspects combined, it is hazardous if I utilize m-banking apps [22, 26, 112, 156].

3.4.9 Confirmation

Confirmation construct is measured by three indicators taken from previous studies [19, 20, 112], and these indicators are the following: (1) Utilizing m-banking apps was more promising than what I desired, (2) M-banking apps service level was better than what I anticipated; and (3) Altogether, most of my anticipations from utilizing m-banking apps were confirmed.

3.4.10 Satisfaction

The statements that are used by this study to estimate the satisfaction of elderly citizens with using m-banking apps are: (1) I determined to use m-banking apps; (2) My decision to utilize m-banking apps was excellent; and (3) I believe that my choice to utilize m-banking apps was accurate [19, 20, 112].

3.4.11 Continuance usage intention

The Items of continued usage intention are adapted from Bhattacharjee (2001a, b), which are: (1) I like to persist in utilizing m-banking apps instead of abandoning, (2) I prefer to continue using m-banking apps instead of any alternative ways; and (3) I intend to suggest m-banking apps to my friends and family.

3.5 Common method variance (CMV)

Common method variance (CMV) happens if the same survey method is applied to dependent variables and independent variables [15]. As CMV significantly affects data reliability and integrity [72], Harman's single-factor test for CMV is advised by Podsakoff et al. [110]. If the CMV value for the single component is more than 50%, then it is expected that the study has a common method bias [97]. In this study, the CMV value is 20%, far less than the threshold value. To further strengthen the CMV assessment, a full collinearity test was conducted following Kock [80], which is considered a more robust diagnostic for common method bias. All Variance Inflation Factor (VIF) values for the predictor constructs are well below the threshold of 3.3: IQ = 1.208, SYQ = 1.296, SQ = 1.238, EE = 1.314, PE = 1.509, SI = 1.054, TR = 1.397, and PR = 1.262. These results confirm the absence of common method bias at both the item and construct levels. Additionally, procedural remedies were employed at the design stage: measurement items for independent and dependent constructs were presented in randomized blocks, and respondents were assured of anonymity to minimize social desirability bias. Accordingly, there is no common method bias, and the data is reliable.

4 Empirical results

4.1 Respondents' demographic profile

Table 1 contains the demographic information of the respondents. Among 160 respondents, 53% are female, and 47% are male, along with 53% of respondents who are from 66 to 70 years old. Besides, 53% of the people surveyed have mobile usage experience for more than ten years, while 47% of them have M-banking app usage experience for 1–3 years.

4.2 Reflective measurement model results—reliability and validity

Construct loading examination is the rudimentary stage in measurement model assessment [50]. Convergent and discriminant validity are two vital tools for measuring the outer model. Composite Reliability (CR) and the Average Variance Extracted (AVE) are applied to measure Convergent validity [4, 50].

According to Hair et al. [49, 54], CR and AVE threshold values should be 0.70 and 0.50, respectively. For this study, both CR and AVE values met the threshold value for all constructs, as shown in Table 2. Hence, the convergent validity of this study is affirmed Hair et al. [49, 54]. The values of CR and AVE determine whether to remove weaker indicators having a loading of 0.40–0.70 [29]. The CR values of this study are greater than 0.70, which ascertains reliability. Following Hair et al. (2017), indicators with loadings between 0.40 and 0.70 may be retained when their removal does not meaningfully improve the AVE or CR of the respective construct beyond their thresholds, and when the indicator contributes unique and theoretically justified content. In this study, several indicators fall below the commonly cited threshold of 0.708, specifically EE1 (0.558), PE1

Table 1 Socio-demographic profile of respondents (N = 160)

Demographic variable	Frequency	Percentage (%)
<i>Gender</i>		
Male	75	47
Female	85	53
<i>Age (Years)</i>		
60–65	15	9
66–70	85	53
71–75	58	36
76–80	2	1
<i>Educational qualification</i>		
Higher Secondary	36	23
Bachelor's degree	71	44
Master's degree	53	33
<i>Mobile phone usage experiences</i>		
Less than 1 year	2	1
1–5 years	6	4
6–10 years	67	42
More than 10 years	85	53
<i>M-banking apps usages experiences</i>		
Less than 1 years	61	38
1–3 years	75	47
4–6 years	22	14
More than 6 years	2	1
<i>M-banking usage frequency</i>		
Once per week	17	11
Once per month	50	31
2–5 times per month	73	46
More than 5 times per month	20	13
<i>Income Level</i>		
Less than BDT 25,000	52	33
BDT 25,001–BDT 50,000	41	26
BDT 50,001–BDT 75,000	29	18
Above BDT 75,000	38	24

(0.582), STF1 (0.648), PR1 (0.649), and SYQ1 (0.591). It was verified that removing each of these items does not increase the AVE or CR of the respective construct to a degree that would alter conclusions, and each item represents a conceptually distinct facet of its construct as established in the original validated scales [34, 112, 151]. Accordingly, all indicators were retained. Table 2 represents latent variables' reliability, while Tables 3, 4, and 5 depict discriminant validity.

Several measures are utilized to ensure the discriminant validity of this research, such as the Fornell-Larcker Criterion, Cross-loadings, and HTMT₉₀ Criterion. As suggested by Fornell & Larcker [39], to meet the requirement of discriminant validity, the diagonal values must be higher than the off-diagonal values, and this study has sufficient discriminant validity as all constructs satisfy the criteria. Table 4 demonstrates discriminant validity using the HTMT₉₀ criterion. All constructs met HTMT₉₀ criterion, and it could be confirmed that the study had discriminant validity [1, 60]. Table 5 shows the cross-loadings of constructs, and as per the recommendation, the loadings of an indicator must be higher than the cross-loading of the indicator [87].

Table 2 Validation result of measurement model

Latent variables	Indicators	Loadings	AVE	CR
Confirmation	CON1	0.806	0.60	0.82
	CON2	0.789		
	CON3	0.732		
Continued usage intention	COUI1	0.750	0.56	0.79
	COUI2	0.752		
	COUI3	0.739		
Effort expectancy	EE1	0.558	0.58	0.80
	EE2	0.815		
	EE3	0.875		
Information quality	IQ1	0.721	0.56	0.79
	IQ2	0.821		
	IQ3	0.700		
Perceived risk	PR1	0.649	0.52	0.76
	PR2	0.704		
	PR3	0.802		
Performance expectancy	PE1	0.582	0.56	0.79
	PE2	0.802		
	PE3	0.834		
Satisfaction	STF1	0.648	0.53	0.77
	STF2	0.808		
	STF3	0.722		
Service quality	SQ1	0.740	0.56	0.79
	SQ2	0.833		
	SQ3	0.658		
Social influence	SI1	0.727	0.61	0.82
	SI2	0.833		
	SI3	0.779		
System quality	SYQ1	0.591	0.55	0.78
	SYQ2	0.864		
	SYQ3	0.746		
Trust	TR1	0.731	0.57	0.80
	TR2	0.766		
	TR3	0.759		

Table 3 Fornell-Larcker criterion

Latent variables	CON	COUI	EE	IQ	PR	PE	STF	SQ	SI	SYQ	TR
CON	0.776										
COUI	0.630	0.747									
EE	0.258	0.265	0.762								
IQ	0.256	0.232	0.248	0.749							
PR	−0.442	−0.415	−0.169	−0.240	0.721						
PE	0.381	0.342	0.366	0.195	−0.323	0.748					
STF	0.594	0.568	0.220	0.236	−0.435	0.332	0.729				
SQ	0.257	0.260	0.214	0.220	−0.133	0.379	0.246	0.747			
SI	0.162	0.233	0.069	0.144	−0.123	0.040	0.228	0.162	0.781		
SYQ	0.323	0.186	0.396	0.256	−0.225	0.318	0.230	0.220	0.033	0.742	
TR	0.437	0.327	0.251	0.308	−0.387	0.409	0.291	0.235	0.104	0.268	0.752

4.3 Assessment of the structural model results

Assessing collinearity issues is the initial stage in evaluating the structural model. A Variance Inflation Factor (VIF) of under three is advised to confirm the absence of collinearity [25]. The VIF values for the study's independent variables are 1.208, 1.296,

Table 4 Heterotrait–Monotrait ratio (HTMT₉₀)

Latent variables	CON	COUI	EE	IQ	PR	PE	STF	SQ	SI	SYQ	TR
CON	–										
COUI	0.895	–									
EE	0.342	0.385	–								
IQ	0.382	0.373	0.392	–							
PR	0.734	0.734	0.265	0.418	–						
PE	0.563	0.558	0.547	0.326	0.546	–					
STF	0.879	0.864	0.352	0.393	0.806	0.581	–				
SQ	0.402	0.415	0.341	0.374	0.247	0.574	0.497	–			
SI	0.229	0.358	0.216	0.216	0.280	0.151	0.374	0.267	–		
SYQ	0.486	0.317	0.570	0.460	0.412	0.510	0.393	0.464	0.246	–	
TR	0.679	0.545	0.337	0.492	0.688	0.653	0.502	0.393	0.231	0.431	–

Table 5 Cross loadings

Indicators	CON	COUI	EE	IQ	PE	PR	SI	SQ	STF	SYQ	TR
CON1	0.806	0.499	0.194	0.286	0.281	−0.350	0.159	0.161	0.532	0.189	0.331
CON2	0.789	0.464	0.155	0.213	0.289	−0.318	0.030	0.212	0.395	0.249	0.346
CON3	0.732	0.499	0.246	0.093	0.317	−0.357	0.175	0.229	0.444	0.317	0.340
COUI1	0.463	0.750	0.157	0.168	0.193	−0.325	0.217	0.080	0.394	0.217	0.328
COUI2	0.464	0.752	0.273	0.230	0.280	−0.348	0.144	0.188	0.425	0.158	0.280
COUI3	0.484	0.739	0.163	0.125	0.286	−0.260	0.166	0.298	0.451	0.053	0.137
EE1	0.051	0.055	0.558	0.182	0.218	−0.099	0.186	0.100	0.101	0.160	0.074
EE2	0.199	0.180	0.815	0.210	0.337	−0.124	0.016	0.217	0.188	0.351	0.204
EE3	0.253	0.279	0.875	0.201	0.287	−0.157	0.062	0.158	0.190	0.337	0.234
IQ1	0.194	0.136	0.069	0.721	0.183	−0.148	0.112	0.171	0.201	0.194	0.145
IQ2	0.228	0.223	0.265	0.821	0.110	−0.218	0.129	0.134	0.204	0.230	0.306
IQ3	0.135	0.153	0.226	0.700	0.160	−0.169	0.071	0.215	0.105	0.132	0.235
PE1	0.192	0.250	0.233	0.196	0.582	−0.106	0.074	0.122	0.226	0.130	0.246
PE2	0.255	0.252	0.236	0.061	0.802	−0.256	0.033	0.326	0.295	0.232	0.312
PE3	0.368	0.273	0.334	0.186	0.834	−0.314	0.006	0.352	0.240	0.310	0.348
PR1	−0.285	−0.301	−0.106	−0.228	−0.165	0.649	0.025	−0.070	−0.344	−0.183	−0.288
PR2	−0.312	−0.267	−0.119	−0.110	−0.281	0.704	−0.166	−0.161	−0.293	−0.177	−0.305
PR3	−0.355	−0.328	−0.139	−0.187	−0.247	0.802	−0.113	−0.060	−0.310	−0.134	−0.253
SI1	0.102	0.146	0.064	0.125	0.116	−0.066	0.727	0.092	0.147	−0.011	0.165
SI2	0.141	0.259	0.021	0.118	0.042	−0.181	0.833	0.105	0.207	−0.009	0.123
SI3	0.131	0.130	0.082	0.098	−0.047	−0.029	0.779	0.178	0.174	0.092	−0.028
SQ1	0.207	0.205	0.273	0.134	0.319	−0.107	0.091	0.740	0.226	0.136	0.127
SQ2	0.210	0.213	0.089	0.218	0.307	−0.067	0.086	0.833	0.154	0.134	0.198
SQ3	0.153	0.157	0.108	0.137	0.210	−0.137	0.212	0.658	0.171	0.250	0.214
STF1	0.324	0.382	0.221	0.218	0.235	−0.300	0.227	0.282	0.648	0.140	0.224
STF2	0.451	0.472	0.122	0.200	0.240	−0.324	0.207	0.218	0.808	0.216	0.254
STF3	0.507	0.386	0.154	0.109	0.253	−0.328	0.078	0.061	0.722	0.142	0.163
SYQ1	0.139	0.073	0.248	0.299	0.250	−0.149	0.026	0.340	0.129	0.591	0.149
SYQ2	0.295	0.128	0.277	0.121	0.202	−0.149	−0.102	0.103	0.180	0.864	0.233
SYQ3	0.251	0.199	0.365	0.227	0.289	−0.212	0.174	0.152	0.196	0.746	0.203
TR1	0.331	0.175	0.059	0.215	0.287	−0.255	0.043	0.207	0.244	0.085	0.731
TR2	0.315	0.273	0.218	0.229	0.321	−0.394	−0.001	0.123	0.237	0.257	0.766
TR3	0.338	0.290	0.289	0.250	0.315	−0.231	0.186	0.196	0.178	0.263	0.759

bold and italic values represent the highest loading of each indicator on its respective construct

1.238, 1.314, 1.509, 1.054, 1.397, 1.262, 1.000, and 1.000 for IQ, SYQ, SQ, EE, PE, SI, TR, PR, CON, and STE, respectively, as shown in Table 6. Since VIF values for all variables met the standard value, the study has no collinearity issues [53].

The structural model with path coefficients is represented in Fig. 2. A bootstrapping procedure has been adopted to predict the β , t-score, significance level (p -values), and R^2 for the inner model, as displayed in Table 6 [49, 54, 55]. The bootstrapping results indicate support for H2, H7, H8, H9, and H10, while H1, H3, H4, H5, and H6 are deemed insignificant and not supported. System quality ($\beta = 0.128$, $t = 1.723$, $p = 0.042 < 0.050$, $f^2 = 0.019$), trust ($\beta = 0.206$, $t = 2.698$, $p = 0.003 < 0.050$, $f^2 = 0.046$), and perceived risk ($\beta = -0.260$, $t = 3.432$, $p = 0.000 < 0.050$, $f^2 = 0.081$) have positively significant consequence on confirmation variable. Besides, confirmation ($\beta = 0.594$, $t = 11.868$, $p = 0.000 < 0.050$, $f^2 = 0.546$) has a positively significant impact on satisfaction, and satisfaction ($\beta = 0.568$, $t = 10.026$, $p = 0.000 < 0.050$, $f^2 = 0.477$) also has a positively significant impact on continued usage intention. The P -values of information quality ($p = 0.308$), service quality ($p = 0.174$), effort expectancy ($p = 0.316$), performance expectancy ($p = 0.071$), and social influence ($p = 0.140$) are greater than the cut-off value (0.05). Therefore, information quality, service quality, effort expectancy, performance expectancy, and social influence do not have a statistically significant impact on confirmation.

R^2 and Q^2 values are measured to detect the predictive accuracy and predictive relevance of the study, respectively [51, 52]. For this study, the R^2 values are greater than 0.30, which is slightly higher than the accepted value of 0.25 [62]. Consequently, this study retains predictive accuracy. Q^2 values are more than 0.15, which is greater than zero [44]. Therefore, the model has predictive relevance.

4.4 Multigroup analysis (MGA)

The present study aims to investigate whether respondents' confirmation of mobile banking app usage varies according to their income level. Respondents were divided into two groups based on a monthly income cut-off of BDT 50,000: the low-income group (monthly income below BDT 50,000; $n = 93$) and the high-income group (monthly income of BDT 50,001 and above; $n = 67$). This cut-off is substantively meaningful because it broadly corresponds to the median household income threshold in urban Bangladesh (Bangladesh Bureau of Statistics 2022) and aligns with distinctions in digital service consumption observed in prior research on financial technology use in lower-middle-income contexts [32]. Consequently, the gathered data are classified into two categories according to the respondents' income: low earners and high earners. MGA is to be used if either partial or full invariance is achieved, as suggested by Henseler et al. [61]. Table 7 shows that invariances have been achieved for half of the constructs and have not been achieved for the other constructs. To investigate the differences in the m-banking apps usage confirmation between the low-earner and high-earner groups, a multi-group analysis has been conducted. It is important to note that the MICOM results indicated mixed measurement invariance across groups: some constructs (CON, COUI, PE, STE, TR) achieved full invariance, while others (EE, IQ, PR, SI, SYQ, SQ) showed only partial invariance. Accordingly, the MGA results must be interpreted with appropriate caution, and group comparisons should be understood as indicative rather than definitive. Table 8 depicts the results of the differences between the two groups. Critically, the MGA findings indicate that income acts as a selective moderator rather

Table 6 Path coefficients and hypothesis testing

Hypothesis	Path	Std. β	Std. deviation	t values	p values	5.00%	95.00%	Decision	VIF	R ²	Q ²	f ²
H1	IQ-> CON	0.037	0.074	0.501	0.308	-0.089	0.152	Not Supported	1.208	0.343	0.163	0.002
H2	SYQ-> CON	0.128	0.074	1.723	0.042	0.004	0.249	Supported	1.296			0.019
H3	SQ-> CON	0.071	0.076	0.939	0.174	-0.065	0.184	Not supported	1.238			0.006
H4	EE-> CON	0.037	0.077	0.478	0.316	-0.099	0.155	Not supported	1.314			0.002
H5	PE-> CON	0.122	0.083	1.472	0.071	-0.012	0.258	Not supported	1.509			0.015
H6	SI-> CON	0.080	0.074	1.082	0.140	-0.070	0.185	Not supported	1.054			0.009
H7	TR-> CON	0.206	0.076	2.698	0.003	0.083	0.333	Supported	1.397			0.046
H8	PR-> CON	-0.260	0.076	3.432	0.000	-0.380	-0.135	Supported	1.262			0.081
H9	CON-> STF	0.594	0.050	11.868	0.000	0.497	0.665	Supported	1.000	0.353	0.175	0.546
H10	STF-> COUI	0.568	0.057	10.026	0.000	0.454	0.646	Supported	1.000	0.323	0.168	0.477

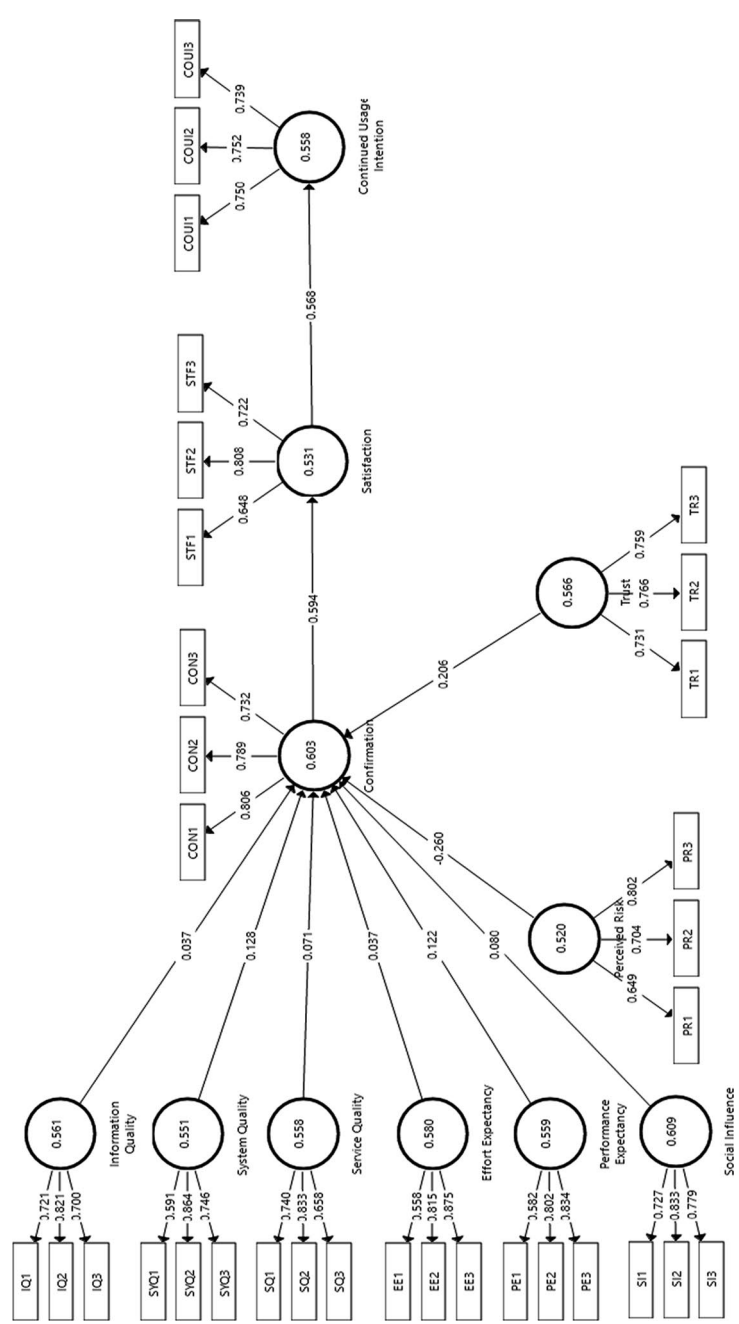


Fig. 2 Structural model for continuance usage intention of m-banking apps

Table 7 Measurement invariance of composite models (MICOM) analysis

Constructs	Compositional invariance (Step 2)			Equal mean examination (Step 3a)			Equal variance examination (Step 3b)			Full mea- surement invariance	
	Original Correlation	5.00%	Permuta- tion p-values	Partial mea- surement invariance	Mean-original difference	Lower limit 5.00%	Upper limit 95.00%	Variance-original difference	Lower limit 5.00%		Upper limit 95.00%
CON	0.997	0.985	0.477	Yes	0.085	-0.261	0.271	-0.230	-0.301	0.268	Yes/Yes
COUI	0.999	0.970	0.917	Yes	0.196	-0.263	0.266	0.064	-0.328	0.302	Yes/Yes
EE	0.983	0.641	0.793	Yes	0.257	-0.274	0.261	-0.375	-0.279	0.257	Yes/No
IQ	0.986	0.627	0.857	Yes	0.274	-0.260	0.264	-0.371	-0.544	0.499	No/Yes
PR	0.977	0.924	0.385	Yes	0.139	-0.271	0.262	-0.389	-0.295	0.279	Yes/No
PE	0.999	0.879	0.964	Yes	-0.069	-0.261	0.266	-0.196	-0.299	0.272	Yes/Yes
STF	0.977	0.970	0.092	Yes	-0.233	-0.269	0.267	-0.298	-0.401	0.367	Yes/Yes
SQ	0.886	0.731	0.230	Yes	0.342	-0.274	0.259	-0.323	-0.287	0.269	No/No
SI	0.985	0.281	0.916	Yes	0.106	-0.266	0.260	-0.487	-0.326	0.295	Yes/No
SVQ	0.900	0.811	0.173	Yes	0.248	-0.276	0.272	-0.487	-0.329	0.300	Yes/No
TR	0.990	0.938	0.604	Yes	-0.062	-0.270	0.258	0.076	-0.361	0.352	Yes/Yes

Table 8 Comparison between the high earner and low earner

Path relationships	Path coefficients original (high earner)	Path coefficients original (low earner)	Std. error (high earner)	Std. error (low earner)	t-Value (high earner)	t-Value (Low earner)	p-Value (High earner)	p- Value (Low earner)
IQ-> CON	0.273	-0.104	0.120	0.088	2.282	1.184	0.011	0.118
SYQ-> CON	-0.216	0.248	0.126	0.086	1.715	2.900	0.043	0.002
SQ-> CON	0.316	0.013	0.109	0.102	2.893	0.132	0.002	0.447
EE-> CON	0.125	-0.008	0.109	0.105	1.141	0.072	0.127	0.471
PE-> CON	0.113	0.146	0.124	0.116	0.911	1.258	0.181	0.104
SI-> CON	0.106	0.079	0.106	0.106	1.007	0.741	0.157	0.229
TR-> CON	0.126	0.234	0.110	0.103	1.139	2.266	0.127	0.012
PR-> CON	-0.278	-0.305	0.114	0.106	2.442	2.880	0.007	0.002
CON-> STF	0.613	0.606	0.079	0.062	7.732	9.736	0.000	0.000
STF-> COUI	0.627	0.580	0.075	0.068	8.308	8.516	0.000	0.000

than a broad, across-the-board differentiator: only three of the ten path relationships differ significantly between income groups, specifically, information quality to confirmation, system quality to confirmation, and service quality to confirmation. The remaining seven path relationships, including effort expectancy, performance expectancy, social influence, trust, perceived risk, confirmation–satisfaction, and satisfaction–continuance intention, do not differ significantly across income groups. This selective pattern suggests that income-based heterogeneity in m-banking confirmation is concentrated specifically in the IS quality dimensions, while the broader motivational and satisfaction–loyalty chain operates similarly across both income segments.

Table 9 shows the findings of the parametric and Welch-Satterthwaite tests to demonstrate equal and unequal differences across groups, respectively. Welch-Satterthwaite is widely used for unequal variances between groups [153]. According to both tests, Welch-Satterthwaite test and the parametric test, the findings reveal notable disparities among the groups concerning the following relationship paths: information quality to confirmation, system quality to confirmation, and service quality to confirmation. However, the remaining relationship paths show no significant impact between the target groups.

5 Discussion and implications

5.1 Theoretical implications of findings

This study investigates the factors affecting the continued intention to use M-Banking apps by elderly citizens in Bangladesh using an integration of the IS success model, ECM, and UTAUT model. From a theoretical standpoint, this study makes several important contributions to the existing literature. First, it is among the first to integrate the IS Success Model [34], the Expectation Confirmation Model [19, 20], and the UTAUT [150] within a unified framework specifically aimed at understanding m-banking app continuance intention among older adults in a developing country context. While prior studies have combined subsets of these theories (e.g., [64, 158]), their joint application with a demographic-specific focus on elderly users in Bangladesh is novel. Critically, the theoretical positioning of UTAUT constructs (effort expectancy, performance expectancy, and social influence) as antecedents of confirmation—rather than of continuance intention directly—is theoretically motivated by the post-adoption logic of ECM: in a continuance context, these constructs are expected to shape whether users feel that the system has met or exceeded their usage expectations (i.e., confirmation), not to independently drive repeat-use intent. For older adults in particular, who tend to have narrower functional expectations of digital banking and higher sensitivity to usability constraints, the UTAUT predictors are theoretically expected to operate upstream through the confirmation channel, filtering into satisfaction and then continuance intention, consistent with Venkatesh et al. [152] and Hidayat-ur-Rehman et al. [64].

Second, the finding that trust and perceived risk significantly shape confirmation—rather than directly influencing satisfaction or continuance intention—refines the nomological network of the ECM, extending its theoretical scope to include contextual risk and trust considerations that are particularly salient for older adults engaging in digital financial transactions.

Third, this study contributes to the digital divide and equity literature by empirically demonstrating through multi-group analysis that IS quality dimensions (information quality, system quality, and service quality) differentially affect the confirmation of

Table 9 Multigroup analysis

Path relationships	Parametric test		Welch-Satterthwaite test			
	Path coefficients-diff (High earner–Low earner)	t-Value (High earner vs Low earner)	p-Value (High earner vs Low earner)	Path Coefficients-diff (High earner–Low earner)	t-Value (High earner vs Low earner)	p-Value (High earner vs Low earner)
IQ-> CON	0.378	2.616	0.005	0.378	2.557	0.006
SYQ-> CON	−0.465	3.180	0.001	−0.465	3.068	0.002
SQ-> CON	0.302	2.011	0.023	0.302	2.042	0.022
EE-> CON	0.132	0.860	0.196	0.132	0.878	0.191
PE-> CON	−0.033	0.191	0.424	−0.033	0.194	0.423
SI-> CON	0.028	0.181	0.428	0.028	0.186	0.427
TR-> CON	−0.108	0.708	0.240	−0.108	0.720	0.237
PR-> CON	0.028	0.176	0.430	0.028	0.178	0.429
CON-> STF	0.007	0.076	0.470	0.007	0.075	0.470
STF-> COUI	0.046	0.455	0.325	0.046	0.459	0.324

m-banking usage between lower- and higher-income elderly users, underscoring the role of socioeconomic heterogeneity in technology continuance behavior. Fourth, by situating the analysis within Bangladesh, a lower-middle-income developing country, the study contributes to the growing body of IS continuance research in non-WEIRD (Western, Educated, Industrialized, Rich, Democratic) contexts, providing a counterpoint to findings predominantly derived from high-income, technologically advanced societies.

System quality and confirmation to use m-banking apps have a positive correlation, as users' intent to use a system depends on the system's reliability, user-friendliness, and familiarity with the system [8, 21, 119, 144]. The underlying reason is that older adults, who tend to have lower digital self-efficacy and narrower functional expectations, evaluate m-banking primarily through the lens of whether it works reliably and predictably. A system that is responsive, stable, and accessible validates their prior decision to adopt, directly generating confirmation that usage was worthwhile. In contrast, system failures or confusing interfaces disproportionately erode the confidence of older users, for whom digital troubleshooting is cognitively costly. Thus, system quality operates as a foundational confirmation driver—not merely because it improves experience abstractly, but because it fulfills the older adult's most basic expectation: that the technology will safely perform its intended function. Trust has a positive impact on confirmation [64, 133, 152]. This finding is theoretically grounded in the unique vulnerability of older adults to digital financial fraud. Elderly users who trust that a banking app is secure, reliable, and institutionally accountable are confirming that the service has met their foundational expectation of safety—an expectation that is particularly salient for a demographic that is acutely aware of online fraud risks and often has limited recourse if a financial loss occurs. The positive trust-confirmation relationship thus reflects a mechanism whereby institutional credibility resolves a pre-existing anxiety, enabling older users to affirm that continued engagement with m-banking is rational and safe.

PR also has a significant but negative effect on m-banking app usage continuation [42, 43, 73, 156]. The deeper theoretical explanation is that perceived risk operates as a cognitive brake on confirmation: when an older adult perceives that a transaction may expose them to fraud, financial loss, or data breach, their retrospective evaluation of usage is colored by anxiety rather than fulfillment. This is especially pronounced among elderly users, who are disproportionately targeted by digital financial scams and who often cannot rely on advanced digital literacy to distinguish legitimate app behavior from anomalies. Unlike younger users who may accept a degree of risk as routine, older adults in developing country contexts, where regulatory consumer protections are less robust, tend to hold zero-risk expectations from financial digital tools. When perceived risk is high, expectations are therefore structurally undermined, and confirmation cannot occur. The negative risk-confirmation relationship thus reflects not merely inconvenience, but a fundamental incompatibility between the older adult's safety expectations and their lived experience of digital financial uncertainty.

This study reports a positive relationship between confirmation and satisfaction, and this association is also supported by other authors [82, 113, 137, 141, 156]. Not only does confirmation of users of m-banking apps have positive consequences on satisfaction, but users of other app categories also emphasize this association [27, 41]. The theoretical reason underlying this pathway is rooted in the expectation-confirmation mechanism: when older adults perceive that their actual experience with m-banking has met or

exceeded what they anticipated, the cognitive dissonance associated with uncertainty is resolved positively, generating an emotional state of satisfaction. For elderly users, this resolution is particularly meaningful because their initial expectations are often conservative and risk-averse. Confirmation therefore acts as a powerful signal that the decision to use m-banking was a good one, reinforcing positive self-evaluation and reducing regret—both of which feed into overall satisfaction and strengthen the motivation to continue.

The relationship between satisfaction and continued usage intention is also supported by this study. Other studies also support this relationship [40, 64, 112, 113, 156]. The reason this pathway is especially robust among older adults lies in the economics of inertia and relationship investment. Having invested cognitive effort, time, and emotional resolve to learn and adopt digital banking, satisfied elderly users are more likely to persist because switching costs—both cognitive and financial—are high. Satisfaction functions as a positive reinforcement signal that validates past investment and reduces the perceived risk of continued use. Moreover, for older adults, who tend to exhibit stronger loyalty orientations and greater habit persistence than younger cohorts, satisfaction also crystallizes behavioral routines that make continuation the default choice rather than an active deliberation.

Although previous studies found a positive association between information quality and confirmation [42, 43, 79] and between service quality and confirmation [3], this study reveals an insignificant impact of information quality and service quality on confirmation. The theoretical reason for this unexpected finding lies in how older adults in Bangladesh cognitively process their m-banking experience. For this demographic, confirmation is anchored to a minimal threshold of functional adequacy, specifically, whether the system performs core transactions (transfers, payments, balance checks) reliably and without error. Information quality, which concerns the accuracy and completeness of data outputs, is only salient to users who actively read and interpret detailed financial information—a behavior more characteristic of financially sophisticated, younger users. Older adults with limited app-usage repertoires are less likely to scrutinize output quality because they are primarily concerned with transaction completion, not informational richness. Similarly, service quality (responsiveness of customer support and follow-up facilities) fails to significantly influence confirmation because these service dimensions are typically accessed only when problems arise, and the majority of respondents reported routine, uneventful usage. When system quality is high and perceived risk is low, older adults achieve a “good enough” confirmation threshold that is decoupled from information and service quality dimensions, which remain latent unless triggered by system failure or service need.

Effort expectancy, performance expectancy, and social influence also do not have a positive relation with confirmation, which is inconsistent with previous studies. A clearer theoretical explanation for this pattern lies in the distinctive cognitive and motivational profile of older adult m-banking users in a developing country context. For this population, the primary reference point for confirmation is not whether the app is easy or useful in an abstract sense, but whether the app’s technical performance is stable and secure enough to fulfill basic financial transactions reliably. When system quality is high and perceived risk is low, as shown to be the dominant confirmation drivers in this study, older adult users reach a threshold of “acceptable confirmation” that is anchored to

functional reliability and risk reassurance, not to efficiency gains or social endorsement. UTAUT constructs such as effort expectancy and performance expectancy become less discriminating in this post-adoption stage because older adults have already scaled down their functional expectations to match their actual usage repertoire (primarily transfers, payments, and balance inquiries). The confirmation judgment is therefore driven predominantly by whether the system works reliably and safely, rather than by whether it exceeds expectations on usefulness or ease of use—constructs that may be more discriminating among younger or more digitally active user segments. This explanation is consistent with cognitive load theory [109], which suggests that users with lower digital fluency conserve cognitive effort by anchoring system evaluation to core performance reliability rather than peripheral feature utility. The insignificant relation between social influence and confirmation is supported by previous studies [85, 118]. M-banking users are usually influenced voluntarily by their own experiences instead of the influences of others [150]. In the post-adoption stage, older users in Bangladesh appear to have internalized their usage routines sufficiently that peer or family influence no longer constitutes a meaningful input into their confirmation assessment. Therefore, social influence does not have a significant influence on the confirmation of usage of m-banking apps.

This study is distinctive because of its focus on older persons as the target group, despite existing studies on the continuance of m-banking applications. Besides, this study investigates income-based MGA in this specific demographic and geographic context, which has not been previously explored in a combined fashion. While the underlying constructs and causal chain are well established in prior continuance research, the income-based heterogeneity test with MICOM-verified MGA represents an incremental yet meaningful contribution to the literature. Importantly, the MGA results reveal that income functions as a selective moderator: the effect of IS quality dimensions (information quality, system quality, and service quality) on confirmation differs significantly between lower- and higher-income groups, while most other path relationships, including the satisfaction–continuance intention link, operate equivalently across income levels. A probable reason for the income-differentiated quality effects is that high-income older adults transact financial activities more frequently and for a wider range of purposes; consequently, they hold higher and more differentiated expectations of app accuracy, responsiveness, and reliability, making IS quality dimensions more decisive for their confirmation experience.

5.2 Practical implications of findings

This study augments banking industry practices by highlighting the factors that influence the confirmation, satisfaction, and intention to continue the usage of m-banking apps among older adults. The practical implications are presented across five key stakeholder groups. First, for commercial banks and m-banking app developers, the findings underscore the primacy of system quality in shaping elderly users' confirmation experiences. Banks should invest in improving system reliability, transaction speed, and interface accessibility for older adults, incorporating design features such as larger fonts, voice-assisted navigation, simplified menu structures, and step-by-step transaction guidance to reduce usability barriers for this demographic. Second, for bank regulators and the Bangladesh Bank, the significant role of perceived risk in negatively affecting confirmation suggests that regulatory mandates requiring transparent data security disclosures,

two-factor authentication, and clear fraud liability policies would be beneficial. Regulators should also consider mandating user-centered design standards for m-banking apps to ensure inclusivity for elderly users. Third, for national policymakers and government agencies, this study highlights the need to integrate elderly-friendly digital financial literacy programs into Bangladesh's national digital inclusion agenda (Digital Bangladesh Vision 2041). Pilot programs in Dhaka could serve as models for scaling digital financial education to secondary cities and rural areas. Fourth, for mobile financial service providers and fintech companies, the finding that trust is a significant driver of confirmation suggests that dedicated senior helplines, 24/7 customer support, and transparent grievance redressal mechanisms would meaningfully build trust and encourage sustained app usage among older adults. Fifth, for NGOs and community organizations working with elderly populations, the study suggests that trusted social networks—including family members, community elders, and local bank branch staff—can serve as effective intermediaries to facilitate m-banking app adoption and continued use. Community-based digital literacy workshops tailored for the 60+ demographic could substantially reduce perceived risk and increase confidence in m-banking apps. Policymakers of banks should put emphasis on system quality, trust, and information quality of distinctive apps to ensure confirmation and, thereby, the satisfaction of users, which ultimately influences their intention to continue. Trust is a critical determinant of usage confirmation, as also supported by previous studies [18, 31]. Trust significantly affects the usage confirmation of technology adoption, especially apps offering financial services.

From these findings, practitioners in banking institutions can be careful about maintaining the trustworthiness of m-banking services so that they can positively attract their customers to use their m-banking apps [94, 117]. Therefore, while developing policies, strategists in banking institutions need to consider trust as a vital factor of both confirmation and satisfaction.

Another contribution of this study is that the findings from the multi-group analysis of the present study may guide banking organizations in designing appropriate m-banking apps that may be customized for different income groups. People from the higher-income class value information quality, system quality, and service quality most. Frequency of usage, range of actions, and service may affect the types of information and services needed by the customers. As people with more income have the probability to use apps more frequently and for a wide range of actions, they require relevant and timely information, and the availability of such information affects their confidence and satisfaction.

Largely, the present study models the factors affecting customers' confirmation of usage of m-banking apps, and this outcome enables decision-makers to develop effective policies to emphasize the required factors so that they can positively drive customers towards their m-banking apps. Besides, banking organizations will benefit from this study by focusing on customer satisfaction, as satisfaction determines whether customers will continue to use an app or not.

6 Limitations and future research directions

The study faces several limitations, which in turn create opportunities for further research work. First, the cross-sectional design of this study captures m-banking continuance intention at a single point in time, which precludes causal inference and cannot

account for changes in user attitudes, satisfaction, or behavior over time. Future studies should adopt longitudinal designs to trace the dynamic evolution of continuance intention across multiple time points, providing a more robust understanding of how trust, risk perceptions, and system quality influence sustained usage. Second, all variables were measured via self-administered questionnaires, introducing the possibility of self-reporting bias, including social desirability bias and recall bias, particularly among older adults who may have difficulty accurately recalling their m-banking experiences. Future research could complement survey data with behavioral usage data obtained directly from financial institutions to enhance objectivity. Third, the study is geographically restricted to the Dhaka metropolitan area. While Dhaka represents the highest concentration of formal m-banking users in Bangladesh, the findings may not be directly generalizable to rural areas, secondary cities, or other regions of the country where digital infrastructure, financial literacy levels, and access to m-banking services differ substantially. Future research should extend sampling to multiple divisions or districts of Bangladesh to enhance generalizability. Fourth, the use of purposive non-probability sampling, while appropriate for accessing a difficult-to-reach elderly population, may introduce selection bias. Future studies should explore more representative sampling strategies, including random sampling of registered m-banking users in collaboration with financial institutions. Fifth, the relatively modest sample size of 160, while meeting PLS-SEM requirements, may limit the robustness and stability of findings in subgroup analyses. Future research should employ larger samples to facilitate more granular income-group, gender-group, and education-group comparisons. Sixth, the study was limited to downloadable bank-issued m-banking apps and did not include mobile financial services (MFS) platforms such as bKash and Nagad. Future research comparing continuance intention across both types of platforms would yield richer insights for the Bangladeshi digital financial ecosystem. Finally, future studies could apply qualitative or mixed-method approaches to gain a deeper contextual understanding of older adults' m-banking experiences, barriers, and coping mechanisms that quantitative surveys may not fully capture.

Besides, in the future, researchers could examine different contexts and the continuance intentions of other smartphone apps. A meticulous study could add more potent determinants and moderating variables to the proposed research model of the study. In addition, cultural differences are a crucial driver for technology adoption and continuation, which would be essential for further empirical work in the m-banking apps area. Moreover, this research model would be employed in the contexts of developed countries and underdeveloped countries.

7 Conclusions

In this information era, the internet, along with the usage of wireless handheld devices, has increased enormously. Consequently, the banking sector moved to digitalization to provide quality services. To survive in the competitive environment, banks introduced m-banking apps and invested a large amount of financial resources in cutting-edge technology. To maximize the payoff from this investment, managers ought to concentrate on the app's users' satisfaction, which in turn leads to repeated use of the app. The study assesses the continuation intent of m-banking app users in Bangladesh, which has not been addressed before. Accordingly, this study contributes indirectly to the sustainable

development agenda by identifying the behavioral conditions, such as system quality, trust, and risk reassurance, under which sustained m-banking usage among older adults can be achieved. By demonstrating how these factors enable long-term digital financial inclusion, the study informs the design of more inclusive digital services, which in turn can support progress toward SDG 1, SDG 8, SDG 9, and SDG 10. It is important to note that the study does not directly measure SDG progress; rather, its contribution is enabling in nature, providing evidence of the antecedents that must be in place for digital finance to better serve older and economically disadvantaged populations. The findings of the study expand the existing literature and assist financial policymakers in maximizing aggregate revenue and utilizing the full potential of m-banking apps in a wider context. Furthermore, the results offer insights for financial institutions and policymakers aiming to design inclusive digital services that support equitable economic participation and advance progress toward the SDGs.

Author contributions

H.A. and A.N.M.S. contributed to the conceptualization and methodology, data collection, data analysis, and the overall writing of the original manuscript. N.J. and R.A.R. contributed to the questionnaire preparation, pilot survey, interpretation of the results, and the overall review and editing of the manuscript. F.D.M. contributed to the introduction, methodology, discussion, review, and editing of the entire manuscript. M.M. contributed to the interpretation of the results, discussion, conclusion, review, and editing.

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Data availability

Data can be made available from the corresponding author upon reasonable request, subject to applicable regulations and institutional policies.

Declarations

Ethics approval

Ethical approval was obtained from the Departmental Ethics Committee for Research Involving Human Subjects at the University of Dhaka (Reference Number: IBDUREC-2024–019) prior to the commencement of data collection.

Consent to participate

Informed consent was obtained from all the respondents, who were assured that their participation in this research was entirely voluntary.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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