Sustainable Futures 10 (2025) 100885

Contents lists available at ScienceDirect

Sustainable Futures

journal homepage: www.sciencedirect.com/journal/sustainable-futures

Measuring the influence of FinTech innovation towards consumers' attitude: Moderating role of perceived usefulness

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A R T I C L E I N F O

Keywords:
FinTech innovation
Consumer attitude
Perceived usefulness
Mobile banking
Structural Equation Modeling (SEM)

A B S T R A C T

The study aims to investigate the contribution of perceived usefulness (PU) in shaping consumer attitudes towards FinTech innovations in Bangladesh. Additionally, this investigation seeks to examine the direct effect of FinTech innovation, including performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), perceived financial risk (PFR), and perceived security risk (PSR) on FinTech service users' attitudes (ATT). This inquiry integrated Technology Acceptance Model (TAM), the Unified Theory of Technology Acceptance and Use (UTAUT), and Perceived Risk Theory (PRT) to develop a theoretical framework. A convenience sampling approach is employed for data collection, and 398 respondents' information is included. However, this research reveals that PE, EE, SI, and FC have affected ATT positively and significantly, while PFR and PSR have weaker but statistically significant impacts on ATT. This study provides insights, both theoretical and practical, for future researchers and policymakers.

1. Introduction

In recent years, the financial services landscape has undergone a profound transformation due to the rise of Financial Technology (FinTech). FinTech, a term that merges finance and technology, encompasses the application of cutting-edge technologies such as blockchain, artificial intelligence (AI), machine learning, cloud computing, and mobile applications to enhance financial services [1,2]. FinTech has revolutionized the way consumers access and manage their finances, making financial services more accessible, cost-effective, and user-friendly [3,4]. The rapid pace of FinTech innovation is primarily driven by the increasing demand for digital solutions, rising consumer expectations, and the need for financial inclusion, particularly in developing economies [5]

Historically, traditional financial systems have been centralized, expensive, and often inaccessible, especially to underserved populations. FinTech, however, seeks to democratize financial services by offering alternatives such as mobile banking, peer-to-peer lending, robo-advisors, and decentralized finance (DeFi), which are not only more accessible but also more affordable [6,7]. Over the past decade, FinTech innovations have gained significant traction, particularly in response to the 2008 global financial crisis, which highlighted the limitations of traditional banking models and fueled the adoption of alternative, technology-driven financial services [6,8].

Despite the growing popularity of FinTech innovations, consumer adoption remains uneven. While a substantial portion of the population is enthusiastic about adopting digital financial services due to their perceived convenience and cost-effectiveness, others express reservations, primarily due to concerns over security, privacy, and the lack of trust in new technologies [9–11]. This disparity in consumer attitudes presents a challenge for FinTech firms aiming to expand their market share and create user-friendly solutions that address the diverse needs and concerns of consumers [12,13]. Therefore, understanding the factors that influence consumer attitudes toward FinTech innovations is

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https://doi.org/10.1016/j.sftr.2025.100885
Received 30 December 2024; Received in revised form 4 April 2025; Accepted 18 June 2025
Available online 19 June 2025

crucial to fostering greater adoption and improving service delivery.

A key determinant in shaping consumer attitudes toward FinTech is the concept of Perceived Usefulness (PU), which refers to the degree to which a consumer believes that using a particular technology would enhance their performance or provide value in their financial activities [14]. While much research has focused on the direct impact of PU on technology adoption [15,16], the moderating role of PU, specifically how it interacts with other factors influencing FinTech adoption, remains underexplored. Given that FinTech encompasses a wide range of technologies and services, understanding how PU moderates the relationships between FinTech attributes (such as performance expectancy, effort expectancy, social influence, facilitating conditions, perceived financial risk, and perceived social risk) and consumer attitudes is vital for developing targeted strategies that foster greater adoption [17,18].

To date, research on FinTech adoption has identified several factors that significantly influence consumer attitudes, including performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), perceived financial risk (PFR), and perceived social risk (PSR) [19,20]. Performance expectancy refers to the degree to which a consumer perceives a FinTech innovation to be useful in improving their financial activities, while effort expectancy pertains to the perceived ease of using the technology [21]. Social influence relates to the impact of social networks and peer groups on adoption decisions, while facilitating conditions refer to the availability of resources and infrastructure required for using FinTech innovations. Perceived financial risk and perceived social risk are associated with concerns about financial loss and social consequences of adopting FinTech services [22].

In Bangladesh, where mobile banking and digital payments are becoming increasingly popular, understanding the interplay between these factors is essential for promoting broader adoption and enhancing financial inclusion [23–26]. According to recent reports, mobile banking users in Bangladesh have grown significantly, with more people relying on mobile money platforms for daily transactions, savings, and remittances [27,28]. However, despite this growth, challenges persist, particularly regarding consumer trust and security concerns. The role of perceived usefulness in moderating the influence of these factors on consumer attitudes is especially important in the context of Bangladesh, where financial literacy and awareness of digital platforms remain limited for certain demographic groups [25].

While substantial research exists on the individual factors influencing consumer adoption of FinTech, the moderating role of perceived usefulness remains underexplored [29,30]. The majority of studies have primarily examined direct relationships between FinTech attributes (such as performance expectancy and effort expectancy) and adoption [19]. However, limited attention has been given to how perceived usefulness interacts with these factors and whether it significantly influences consumer attitudes toward FinTech [31–33]. The existing literature also lacks a comprehensive understanding of the contextual factors affecting adoption in developing economies [34,35], such as Bangladesh, where digital literacy and financial inclusion are pivotal concerns [36].

Therefore, this study seeks to address a critical gap in the literature by examining the moderating role of perceived usefulness in shaping consumer attitudes toward FinTech innovations in Bangladesh. By filling this gap, the study contributes to a more comprehensive understanding of FinTech adoption, refining existing theoretical models and offering deeper insights into consumer behavior in digital financial services. Beyond its theoretical contributions, this research provides practical implications for FinTech providers and policymakers aiming to enhance adoption and promote financial inclusion. Understanding how perceived usefulness moderates key determinants of consumer attitudes will enable FinTech firms to tailor their products and marketing strategies to address user concerns and preferences more effectively. Additionally, policymakers can leverage these insights to design regulatory frameworks that foster innovation while ensuring consumer protection and trust in digital financial services. Given Bangladesh's significant potential for digital financial services to drive economic growth and financial inclusion, this study holds substantial relevance. Furthermore, the findings may offer valuable insights for other emerging economies facing similar challenges in FinTech adoption. By highlighting the factors influencing consumer engagement with digital finance, this study contributes to broader discussions on financial inclusion, digital literacy, and the evolving role of technology in economic development.

2. Theoretical foundation and hypothesis development

2.1. Theoretical foundation

The theoretical foundation of this research framework is based on three prominent theories: the Technology Acceptance Model (TAM), the Unified Theory of Technology Acceptance and Use (UTAUT), and the Perceived Risk Theory. These theories offer extensive perspectives into how users assess new technologies like FinTech and how various factors influence their decision to accept or reject such innovations.

2.1.1. Technology Acceptance Model (TAM)

The period in 1986, the TAM theory was mainly developed due to having some crucial flaws in the theory of reasoned action (TRA). That was put from the standpoint of behavioral psychology, combining the theories of self-efficacy and expectation, and is employed for investigating users' behavioural motives when using solutions [14]. Venkatesh and Bala [37] argued that the TAM theory categorises the elements influencing user cognitive attitude into perceived usefulness and perceived ease of use, and two of these elements have a substantial effect on the new technology acceptance. Since the TAM is easily tailored to the analytic issue and describes the variations in customer propensity to accept technological devices, it has surfaced as one of the most commonly applied approaches in the field of technology acceptance research [38]. Utilizing the most recent IT methods for financial creativity is central to FinTech offerings; as a result, the TAM theory in this research is highly flexible. Nevertheless, the TAM is frequently utilised for technology acceptance in mobile banking for online businesses; the distinctiveness of FinTech services causes a major distinction in the installation handle between the TAM and IT techniques acceptance for conventional online businesses [39].

2.1.2. Unified Theory of Technology Acceptance and Use (UTAUT)

The UTAUT was introduced by Venkatesh et al. [40] for the integration of prior theories on attitudes in the IT mechanisms era, such as the TRA [41], TPB [42], the DOI [43], and the TAM [14] theories. SI, FC, PE, and EE are the four elements that the UTAUT utilises because they are its main indicators of psychological and technological advances and aspirations towards application practice [40]. The theory of UTAUT is widely employed as the theoretical framework in technological acceptance and conducting empirical research on individual behavioural intention[44]. When UTAUT theory is compared with other theories for technology acceptance models, the UTAUT theory indeed achieved a great milestone. Because this theory was tested using a variety of different data sources and proved the model is one of the effective models, it is better than any others. Consequently, the UTAUT theory provides a helpful tool for assessing the prospects of emerging technology acceptance progress. Furthermore, it provides an understanding of the elements that affect adoption, allowing individuals to effectively develop actions for consumer communities that may be more reluctant to embrace technologies [40]. Considering the points mentioned earlier, the UTAUT theory is used for executing our study.

2.1.3. Perceived risk theory

Perceived risk refers to the unavoidable feeling that something unpleasant is going to happen [45]. Individuals' trust and belief in their choices are influenced by the perceived level of threat. The risk of individuals can be described properly with the help of perceived risk theory (PRT). The aspects of PRT may be changed based on the product types. Ryu [46] identified six major risk aspects: safety, performance, financial, time or opportunity, social, and psychological. While researching wireless internet adoption, Li et al. [47] used the above-mentioned factors. They argued that online banking has no negative impact on customers' lives. However, in this study, we use just security and financial risk to examine the customers' attitudes.

2.1.4. Risk and perceived risk in FinTech adoption

Risk perception is a fundamental psychological factor that influences consumer behavior, especially in the context of adopting new technologies such as FinTech [48]. While technological advancements promise numerous benefits, they also bring about various uncertainties and risks that can hinder adoption. For FinTech innovations, perceived risk is a multifaceted construct that encompasses different types of risks that consumers associate with using digital financial services [47].

Financial Risk is one of the most prominent concerns among consumers when adopting FinTech innovations [49]. It refers to the potential for financial loss or unanticipated financial costs arising from using digital financial services [50]. This can include concerns about fraud, scams, or unregulated financial practices that could lead to unexpected financial setbacks [51,52]. Financial risk has been shown to negatively influence consumer attitudes toward FinTech, as individuals are often hesitant to embrace platforms that do not offer sufficient safeguards against such losses [2].

Privacy and Security Risks are closely related to financial risk but are distinct in terms of consumers' concerns about their data [53]. In an increasingly digital world, where personal information is stored and shared online, consumers are understandably concerned about their privacy and the security of their financial data [54]. The fear of data breaches, identity theft, and misuse of personal information can deter individuals from engaging with FinTech solutions. In the study by Johnson et al. [55] and Moghavvemi et al. [56], the authors found that concerns over privacy and security risks were significant barriers to adopting mobile payment systems, even when these platforms offered convenience and lower transaction costs.

Social Risk, on the other hand, refers to the potential for adopting FinTech services to have negative social consequences, such as judgment from peers, stigmatization, or loss of social standing due to the use of new technologies [57]. While financial and security risks are more directly related to the tangible outcomes of using FinTech, social risks are more abstract and relate to the consumer's social environment. This type of risk has been found to affect FinTech adoption, especially among older generations or in collectivist societies, where social harmony and approval are significant factors in decision-making [58].

2.2. Perceived risk and consumer attitudes

The relationship between perceived risk and consumer attitudes is central to understanding FinTech adoption. Attitude is a key determinant in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), both of which highlight how consumer perceptions such as perceived usefulness, perceived ease of use, and perceived risk shape their willingness to adopt new technologies [40]. The perceived risk associated with FinTech services often leads to a negative attitude toward adoption. The studies by [59,60] showed that perceived risk significantly negatively impacted consumers' trust in FinTech services, which in turn affected their intention to use such services. When consumers perceive high levels of risk, whether financial, security, or social, they are less likely to form positive attitudes toward the technology. This negative attitude leads to reduced adoption rates, particularly in countries where digital literacy is lower and trust in online systems is weaker[6]. However, the relationship between perceived risk and attitude is not always straightforward. Recent studies suggest that factors such as perceived usefulness and perceived ease of use can moderate this relationship. For instance, when consumers perceive FinTech services as highly useful in enhancing their financial activities (e.g., mobile payments and investing platforms), they are more likely to overlook certain risks and adopt the technology despite their concerns [54]. Furthermore, consumer trust which can be influenced by the reputation of FinTech firms, regulatory frameworks, and the transparency of service providers, can reduce the perceived risk, thereby improving consumers' attitudes toward adoption [61,62].

2.3. Hypotheses development

2.3.1. Attitude

Attitudes are overall evaluations that individuals hold about people, places, objects, and issues, encompassing feelings, beliefs, and behavioral inclinations[63]. The term attitude was initially used by Jung [64] to prepare to respond to his writings about psychological types. It is thus relevant to various fields, including marketing-related attitudes, advertising-related attitudes, political-related attitudes and health-related attitudes [65]. Attitudes can either be specific or extend across multiple objects, with people generally holding positive or generally negative attitudes[66]. In the FinTech context, attitude is a critical psychological determinant that influences users' intent to adopt or reject innovative financial services [67]. The positive attitude stems from perceived use, utility, and confidence in FinTech services, which significantly increases the adoption rate [68].

On the other hand, negative attitudes stem from skepticism about data security, lack of familiarity or perceived high complexity, hindering potential users [69]. Previous academic studies on FinTech have consistently highlighted the numerous benefits that FinTech innovation brings to both customers and companies[70–72]. While FinTech can provide significant benefits, there are also limitations and disadvantages related to this FinTech innovation. These concerns involve factors such as data breaches, user inertia, ethical dilemmas, beliefs, barriers to acceptance, protecting consumer benefits, and maintaining financial integrity [73,74].

2.3.2. Perceived usefulness (PE) and attitude

Performance expectancy (PE), defined by the UTAUT, focuses on the belief that utilising a particular solution will enhance task performance or improve quality of life [40]. Research indicates that predictive analytics and cost-effective financial solutions increase performance expectancy and positively influence attitudes [75]. Moreover, Srivastava et al. [76] investigated the users' behavioural intention toward the acceptance of digital payment FinTech services in India, and the outcomes of the inquiry concluded that PE significantly affected consumer attitude. When users perceive FinTech as both useful and capable of delivering tangible benefits, their attitudes are significantly more favorable. Roh et al. [60] simultaneously employ the unified theory on "Robo-advisors" and demonstrate that PE has a significant influence on consumer attitudes. Sharma et al. [77] found a strong, significant impact of performance expectancy on attitude. Thus, it is hypothesized that:

H1. Perceived Usefulness (PE) has a significant positive impact on attitude.

2.3.3. Effort expectancy and attitude

Effort expectancy (EE) is the conviction that performance will rise with more effort. Expectancy theory posits that effort is influenced by the values individuals assign to work outcomes and their expectations of achieving those outcomes [78]. Effort is a strong moderator of the attitude-behaviour relationship according to [79], indicating that higher effort correlates with stronger attitudes towards recycling and environmental concern. Rahi et al. [80] integrated the UTAUT model with e-service quality constructs to explore Online banking adoption, revealing that effort expectancy significantly mediates user intentions. Prior research has consistently emphasized the positive impact of effort expectancy on attitude. Rahim et al. [81] argued that reduced EE in using Islamic FinTech services contributes to favourable user attitudes. Similarly, Bajunaied et al. [82] found a significant positive correlation between effort expectancy and the acceptance of FinTech services in Saudi Arabia. Moreover, Srivastava and Mohta [76] highlighted that EE significantly impacted customer satisfaction and attitudes toward digital payment FinTech services. Al Rubaiai and Pria [83] also identified a robust link between effort expectancy and user attitudes in their study on FinTech adoption in Oman. These findings suggest that technologies perceived as easy to use are more likely to garner positive user attitudes, supporting the hypothesis that EE has a noteworthy positive influence on attitude. Thus, it is hypothesized that:

H2. Effort expectancy (EE) has a significant positive impact on attitude.

2.3.4. Social influence and attitude

Individuals' attitudes, behaviors, values, and standards through compliance, identification, and internalization of group norms are significantly shaped by social influence [84]. Likewise, Gass and Seiter [85] emphasise the interplay of persuasion and social influence in attitude formation, noting their profound effects on decision-making processes. Similarly, Spears [86] discusses how key variables like group dynamics and social expectations contribute to the extent of social influence on attitudes, supporting the hypothesis that such influences positively impact individual perspectives. The study investigated FinTech adoption in Lagos, Nigeria, revealing that social influence significantly impacts user attitude [87]. Safitri et al. [88] found that credibility derived from social influence positively impacts intentions to adopt FinTech services in Indonesia, further solidifying its role in shaping user attitudes. Allah Pitchay et al. [89] also found that SI has a strong, significant influence on consumers' attitudes. The consistency across these studies supports the hypothesis that social influence has a significant positive influence on attitudes toward FinTech adoption. Thus, it is hypothesized that:

H3. Social influence has a significant positive impact on attitude.

2.3.5. Facilitating conditions (FC) and attitude

FC implies the availability of resources, infrastructure, and assistance that facilitate the use of technology [90]. When consumers realise that they have enough resources and assistance to use FinTech solutions, their attitude toward adoption is likely to be more positive. Judijanto & Wardhani [91] investigate that favourable conditions such as easy access, technological infrastructure, and assistive services positively impact users' attitudes toward mobile banking applications. Similarly, in the context of e-commerce, facilitating conditions like intuitive interfaces and secure payment systems contribute significantly to forming favourable consumer attitudes [91,92]. Additionally, Lim et al. [58] show that FC in information technology significantly influences the attitude toward mobile internet banking among Gen-Y in Malaysia. For instance, Shin and Biocca [93] found that user attitudes toward mobile banking systems improved when adequate facilitating conditions, such as training and technical support, were present. Similarly, Alalwan et al. [54] emphasised that facilitating conditions significantly influence the acceptance and positive perceptions of FinTech innovations. The availability of FC ensures that users feel supported in their journey toward adopting FinTech innovations. Thus, it is hypothesised that:

H4. Facilitating conditions (FC) have a significant positive impact on attitude.

2.3.6. Perceived security risk and attitude

Consumers prioritise data security and confidentiality when assessing FinTech services, with perceptions of security directly affecting trust levels [94]. A positive attitude towards FinTech-oriented services is essential for encouraging broader adoption among consumers, particularly in regions with emerging FinTech markets [30]. Wijaya et al. [95] showed that users' attitudes towards FinTech are influenced by their perceptions of security risks, impacting their willingness to adopt these technologies. Al-Gasawneh et al. [48] studies indicate that PE negatively impacts financial artificial intelligence services, aligning with findings on perceived security risk affecting attitudes towards FinTech. High levels of perceived security risks can create psychological barriers, causing users to adopt a cautious or negative attitude toward the technology [55]. Similarly, Sreejesh and Anusree [96] discovered that the desire to utilize online banking is negatively influenced primarily by security and privacy concerns. Studies aimed to identify risk factors impacting consumer attitudes towards online shopping in South Africa, using a survey of online consumers at two Gauteng malls, and found that privacy, security, and product risks significantly impacted attitudes according to Makhitha & Ngobeni [97]. Elhajjar & Ouaida [98] also found that security risk has a favourable influence on consumer attitudes. Thus, it is hypothesized that:

H5. Perceived security risk has a significant negative impact on attitude.

2.3.7. Perceived financial risk and attitude

Perceived financial risk refers to the subjective assessment of uncertainty or ambiguity surrounding financial decisions, influenced by affective experiences and feelings [99]. According to Chen [100], perceived financial risk denotes an investor's subjective assessment of the potential for loss in structured financial products, influenced by psychological factors such as overconfidence, which can lead to underestimating risk and overestimating the likelihood of favourable returns. In the FinTech context, perceived financial risk acts as a barrier to adoption, as consumers often associate innovative financial services with uncertainties and potential vulnerabilities [37]. For instance, mobile payment systems, blockchain technologies, and digital wallets have all faced scrutiny due to perceived risks, which subsequently affected user attitudes negatively [101]. Similarly, Hong et al. [57] examined various risks, including financial risk, and found that this often overlaps with financial concerns, negatively affecting customer attitudes toward online shopping. Similarly, Taherdoost [102] emphasized that PE, including financial risk, acts as a key constraint to e-service acceptance. Thus, it is hypothesized that:

H6. Perceived financial risk has a significant negative impact on attitude.

2.3.8. Moderating role of perceived usefulness (PU)

Perceived usefulness (PU) refers to the belief that using technology will lead to better performance and is a core determining factor of acceptance in technology acceptance [103]. This relationship is amplified by a positive attitude, which reinforces the perceived value of FinTech [45,104]. Numerous studies have emphasised PU as a key factor of technology adoption, particularly in moderating the relationships between core technological and social constructs and user attitudes [40]. For instance, Wu and Chen [105] found that users are more likely to develop favourable attitudes toward technology when they perceive high utility and performance benefits. Users with favourable attitudes are more prone to perceive FinTech services as beneficial and align their behavioural intentions accordingly [106].

EE refers to the level of comfort linked with the use of technology, which is essential in fostering initial adoption [104,107]. However, this effect is strengthened when perceived usefulness is high, demonstrating that users are more prone to value ease of use when they see the technology as genuinely beneficial [103]. Studies indicate that the interplay between EE and PU shapes attitudes, particularly for less tech-savvy users [22,45]. Other studies recommend that users are more prone to adopt innovations when they perceive the effort required to be low and the usefulness to be high [15].

SI refers to the degree to which individuals perceive those significant others (e.g., family, friends, or peers) believe they ought to use a specific technology [42]. In the FinTech context, SI plays a critical role in determining attitudes by reinforcing the perceived legitimacy and necessity of adopting financial innovations [60]. However, the strength of this relationship is often contingent upon other aspects, such as PU. For instance, Venkatesh et al. [40] argue that when consumers perceive technology as highly useful, the positive impact of social influence on attitudes becomes more pronounced, as usefulness validates the recommendations of social referents.

FC refers to the accessibility of resources and infrastructure that support technology use [40]. These conditions lower perceived barriers and increase consumer self-confidence in using FinTech platforms. While facilitating conditions are positively linked to attitudes, their impact is magnified when the technology in question is perceived as useful. As highlighted by Jafri et al. [108], PU moderates the relationship between facilitating conditions and attitudes by reinforcing the perception that supportive resources effectively contribute to performance enhancement, (Fig. 1).

H7. Perceived Usefulness (PU) plays a significant moderating role between PE and attitude.

H8. Perceived Usefulness (PU) plays a significant moderating role between EE and attitude.

H9. Perceived Usefulness (PU) plays a significant moderating role between SI and attitude.

H10. Perceived Usefulness (PU) plays a significant moderating role between FC and attitude.

3. Methodology

This study adopts a quantitative research approach, which is suitable for examining relationships between variables systematically and objectively. Quantitative research enables the collection of numerical data, allowing for statistical analysis and hypothesis testing, which enhances the reliability and generalizability of findings [106,109]. It is particularly useful for studies that seek to measure constructs, establish causal relationships, and analyze patterns across large datasets [56]. Furthermore, a quantitative approach ensures a structured and replicable methodology, minimizing researcher bias and enhancing the validity of results [110]. By employing statistical techniques such as Structural Equation Modeling (SEM), this approach allows for the examination of complex relationships between latent variables, making it an effective method for testing theoretical models [111]. Given its ability to provide empirical evidence and support theoretical generalizations, the quantitative approach is well-suited for this study's objectives [75].

3.1. Research design and approach

This study adopts a descriptive cross-sectional research design, which is appropriate for analyzing relationships between variables at a single point in time. A descriptive design allows for an in-depth understanding of patterns, characteristics, and associations without manipulating study variables, making it suitable for exploring perceptions and behaviors in real-world contexts [112]. By systematically collecting data from a sample population, this design helps identify trends and correlations, providing a comprehensive snapshot of the studied phenomenon [75]. A cross-sectional design is particularly effective for studies that aim to assess attitudes, behaviors, or factors influencing decision-making at a specific moment [110]. It enables researchers to analyze diverse participant responses efficiently and is often used in survey-based research due to its cost-effectiveness and practicality in large-scale data collection [113]. Given its ability to generate statistically significant insights without requiring long-term follow-up, the descriptive cross-sectional approach is well-suited for this study's objectives [67].

3.2. Population, sampling, and sample size

The target population for this study consists of FinTech service users in Bangladesh. The population of FinTech users was drawn from individuals who have actively engaged with these services in the past six months, ensuring that the sample represents a knowledgeable group regarding FinTech adoption. A convenience sampling method was employed to collect data from FinTech service users, which is common in studies where time or resource constraints limit access to a more randomized sample [114]. This method, although less rigorous than probability sampling, ensures practical data collection while still yielding insightful results regarding user attitudes and behavior [110]. Convenience sampling was chosen due to the accessibility of respondents through social media platforms, which have a high concentration of FinTech users [115]. Data were collected between September and November 2024, with a total of 410 responses gathered. After a thorough review, 12 invalid and unreliable responses were excluded from the dataset, resulting in a final sample size of 398 valid responses, which is deemed appropriate for SEM analysis [116]. In addition, based on Krejcie & Morgan [117], 398 sample size is justified for the

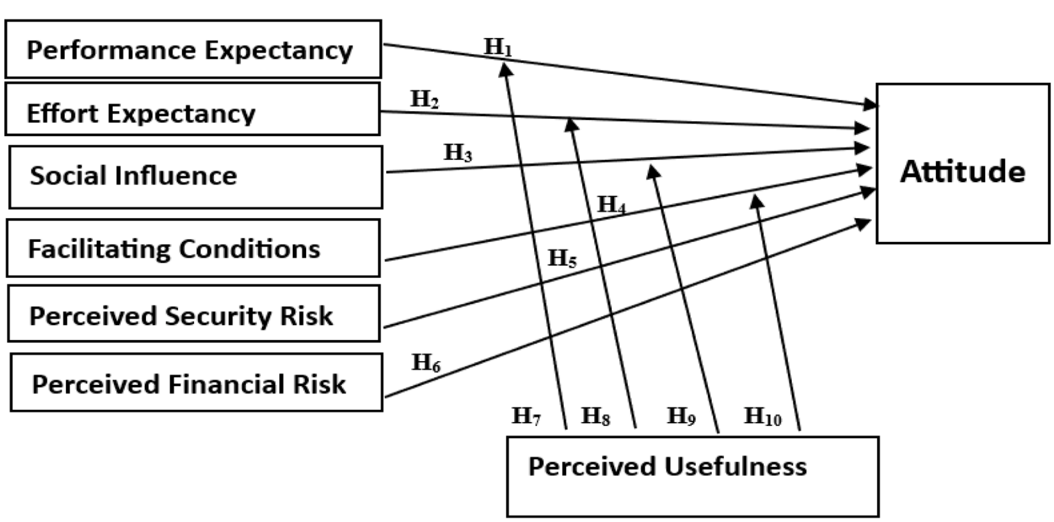

Fig. 1. Conceptual framework.

quantitative research, which is the case here.

3.3. Instrument design

Table 1 shows the measurement scales of this study. The items are somewhat modified based on research objectives. This study uses a 7-point Likert scale to measure all items. Perceived usefulness is adapted from an existing study [14], and it has 5 items. Performance expectancy, effort expectancy, social influence, and facilitating conditions of UTAUT theory [37,40], are employed, and they have 4 items each. Perceived financial risk [118,119] and perceived security risk [120,121] are adapted from the existing study and each construct has 4 items. Attitude is adapted from the existing study [14] and it has 4 items, which is the ultimate goal of the study. All of the variables are shown in Fig. 1.

3.4. Data analysis

Given the focus on FinTech innovations and the consumer behaviors surrounding their adoption, Structural Equation Modeling (SEM) is applied as it allows for the examination of complex relationships between latent variables and their indicators [122]. SEM is particularly useful in analyzing path relationships, which is key for testing the hypotheses related to the impact of perceived usefulness on consumer attitudes [116]. Additionally, Partial Least Squares-Structural Equation Modeling (PLS-SEM) software (SmartPLS 4.0.8.9) is used for data analysis, as it is an appropriate tool for analyzing large datasets with relatively small samples [123]. To evaluate the validity and reliability of the measurement model, both convergent validity and discriminant validity were assessed. Convergent validity was ensured through high loadings of indicators on their respective constructs [116]. Discriminant validity was tested using the Heterotrait-Monotrait ratio (HTMT), ensuring that the constructs were distinct from one another [124]. Additionally, the structural model was assessed by evaluating the path coefficients, R-squared values, and Q-squared values to determine the explanatory power and predictive relevance of the model [116].

4. Results and analysis

4.1. Respondents' characteristics

Table 2 shows the respondents' demographic information. Most respondents in this study are male (69.6 %). 54.4 % of participants' ages are 20–29. Almost 54.0 % of respondents hold a master's degree, and 45.5 % are students by profession. 100 % of respondents hold FinTech innovation literacy.

4.2. Evaluation of common method bias (CMB)

The full collinearity (FC) test for each item indicated that the variance inflation factor (VIF) values ranged from 1.336 to 3.212 (refer to Table 3), falling below the 3.3 threshold [125]. (Kock & Lynn, 2012). Consequently, the results suggest that the study was not impeded by the CMB issue.

4.3. Evaluation of measurement model

The assessment of internal consistency and convergent validity involves evaluating the reliability and validity of the constructs in a research model. This analysis employs the composite reliability (CR), average variance extracted (AVE), and item loadings to ascertain the robustness of the measurement model. Table 3 below serves as essential indicators of the internal structure of the constructs.

Internal consistency is assessed using composite reliability (CR). CR values exceeding the threshold of 0.70 are indicative of reliable constructs (Hair et al., 2010). Across all constructs in the analysis, the CR values meet or exceed this benchmark, confirming strong internal

Table 1
Measurement scales.

Construct	Items	Source
Perceived Usefulness	PU1: FinTech service increases my job performance. PU2: FinTech solutions save me time. PU3: FinTech solutions help me to do my tasks quickly. PU4: FinTech solutions increase my productivity in managing financial transactions. PU5: Overall, I find the FinTech solutions are more useful than traditional banking systems for managing my finances.	[14]
Attitude	ATT1: Using FinTech services is a good decision for managing my financial transactions ATT2: I believe that utilizing FinTech innovations for financial transactions is a wise decision ATT3: I find the experience of using FinTech services to be pleasant ATT4: In my opinion, it is desirable to adopt FinTech innovations for improved financial management	[14]
Performance Expectancy	PE1: FinTech services enable me to manage my banking tasks more efficiently PE2: FinTech services improve the quality of my banking transactions PE3: I achieve better financial outcomes by using FinTech services PE4: FinTech innovations enhance my overall banking experience	[40]
Effort Expectancy	EE1: My interaction with the FinTech system would be clear and understandable EE2: It would be easy for me to become skilful at using the FinTech system EE2: Navigating FinTech platforms is simple EE4: FinTech applications are user-friendly and intuitive	[40]
Social Influence	SI1: My friends and family believe I should use FinTech services for banking SI2: Social recommendations influence my decision to use FinTech services SI3: The opinions of others impact my use of FinTech services SI4: I feel encouraged by my peers to adopt FinTech solutions for banking	[37]
Facilitating Conditions	FC1: I have access to the necessary resources to use FinTech services effectively FC2: Technical support is available when I encounter issues with FinTech services FC3: I have the required skills and knowledge to use FinTech applications FC4: The infrastructure supports my use of FinTech services for banking	[37]
Perceived Financial Risk	PFR1: I am concerned about the potential financial risks associated with using FinTech services for banking PFR2: I worry that FinTech services might expose me to financial losses due to security breaches PFR3: I am concerned that I might be overcharged for certain services when using FinTech platforms PFR4: My confidence in FinTech services is affected by the potential risk of fraudulent activities	[118, 119]
Perceived Security Risk	PSR1: I am concerned about the security of my personal information when using FinTech services PSR2: I worry that my financial data may be accessed by unauthorized individuals when using FinTech services PSR3: The privacy of my financial information is at risk when using FinTech services PSR4: I worry that FinTech platforms could be vulnerable to cyberattacks that may compromise my financial security	[120, 121]

Table 2
Demographic profile of the respondents.

	Frequency	Percent	Cumulative percent
Gender			
Male	277	69.6	69.6
Female	121	30.4	
Total	398	100.0	100.0
Age			
20–29	217	54.4	54.4
30–39	146	36.8	91.2
40–49	23	5.8	97.0
50 and above	12	3.0	
Total	398	100.0	100.0
Educational Level			
Bachelor	138	34.7	34.7
Masters	215	54.0	88.7
Doctorate	40	10.0	98.7
Others	5	1.3	100.0
Total	398	100.0	
Occupation			
Student	181	45.5	45.5
Service holder	159	39.9	85.4
Self-employed	48	12.1	97.5
Others	10	2.5	100.0
Total	398	100.0	
Experience in FinTech service			
Yes	398	100.0	100.0
No	0	0.0	0.0

Table 3
Assessment of internal consistency, convergent validity and collinearity.

Constructs	Item	Loadings	FC	CR	AVE
Attitude	ATT1	0.787	1.806	0.914	0.726
	ATT2	0.869	2.337		
	ATT3	0.889	2.459		
	ATT4	0.859	2.347		
Effort Expectancy	EE1	0.828	1.765	0.895	0.681
	EE2	0.834	2.123		
	EE3	0.859	2.120		
	EE4	0.779	1.646		
Facilitating Condition	FC1	0.788	1.492	0.841	0.57
	FC2	0.693	1.467		
	FC3	0.739	1.336		
	FC4	0.794	1.504		
Performance Expectancy	PE1	0.771	1.676	0.869	0.624
	PE2	0.826	2.063		
	PE3	0.832	1.841		
	PE4	0.724	1.408		
Perceived Financial Risk	PFR1	0.939	2.927	0.973	0.9
	PFR2	0.966	3.212		
	PFR3	0.946	2.303		
	PFR4	0.943	3.014		
Perceived Security Risk	PSR1	0.957	3.121	0.979	0.92
	PSR2	0.967	2.976		
	PSR3	0.955	3.127		
	PSR4	0.956	2.568		
Perceived Usefulness	PU1	0.784	1.867	0.906	0.658
	PU2	0.777	1.797		
	PU3	0.838	2.103		
	PU4	0.835	2.211		
	PU5	0.819	1.990		
Social Influence	SI1	0.807	1.590	0.884	0.656
	SI2	0.844	2.223		
	SI3	0.816	2.084		
	SI4	0.772	1.692		

ATT=Attitude, EE=Effort Expectancy, FC=Facilitating Condition, PE=Performance Expectancy.
PFR=Perceived Financial Risk, PSR=Perceived Security Risk, PU=Perceived Usefulness, FC=Full Collinearity, CR=Composite Reliability, AVE=Average Variance Extracted.

consistency. For instance, constructs such as Attitude (CR = 0.914), EE (CR = 0.895), and PE (CR = 0.869) demonstrate excellent reliability, while PFR (CR = 0.973) and PSR (CR = 0.979) exhibit exceptional internal consistency. Convergent validity is examined using item loadings and average variance extracted (AVE). The AVE should exceed 0.50 to confirm convergent validity (Fornell & Larcker, 1981), and individual item loadings should ideally exceed 0.7 [123] (Hair et al., 2010). Across all constructs, most item loadings exceed 0.7, demonstrating strong relationships between observed variables and their respective latent constructs. Item loadings generally exceed the acceptable threshold of 0.7, reflecting strong relationships between observed variables and their respective latent constructs, with particularly high values for perceived financial risk (all loadings > 0.93). The AVE values for all constructs surpass the minimum requirement of 0.50 (Fornell & Larcker, 1981), indicating that the constructs explain sufficient variance in their indicators. Attitude (AVE = 0.726), PU (AVE = 0.658), and SI (AVE = 0.656) confirm good validity, while FC (AVE = 0.57), despite being on the lower side, still meets the acceptable threshold. These results affirm the reliability and validity of the measurement model, supporting its suitability for further structural analyses. Constructs with exceptionally high reliability and validity, such as PFR and PSR, highlight the strength of the model, while areas like FC suggest potential opportunities for refinement. The findings confirm the internal consistency and convergent validity of the measurement model. All constructs meet the required thresholds for CR and AVE, while item loadings are largely within acceptable limits. Results demonstrated in Table 3 suggest that the constructs are reliable and valid for further SEM and other advanced analyses.

Discriminant validity (DV) confirms that an aspect is distinct from other aspects in a model, thereby confirming that each construct captures unique aspects of the phenomenon being studied. The heterotrait-monotrait ratio of correlations (HTMT) is a robust method for assessing discriminant validity. According to Henseler et al. [126], HTMT values should generally be below 0.90, though stricter thresholds of 0.85 are sometimes applied for conceptually distinct constructs. In this model, the HTMT values are evaluated across constructs to confirm their discriminant validity. The analysis reveals that all HTMT values fall below the conservative threshold of 0.85, supporting discriminant validity across constructs. For example, the HTMT between attitude (ATT) and EE is 0.622, which is well below the threshold, indicating a clear distinction between these constructs. Similarly, the relationship between attitude (ATT) and FC is 0.583, again confirming DV. Other construct pairs, such as EE and FC (HTMT = 0.799), and PE and FC (HTMT = 0.817), also exhibit acceptable levels of HTMT, demonstrating that these constructs are not excessively overlapping. Constructs with inherently higher correlations, such as EE and PE (HTMT = 0.771), still maintain discriminant validity as their HTMT value does not exceed the threshold. Importantly, constructs such as PFR and PSR show low HTMT values with other constructs, such as 0.894 between PFR and PSR, which supports the conceptual separation between financial and security risk perceptions. Moreover, the HTMT between PU and EE (HTMT = 0.682) as well as between SI and FC (HTMT = 0.687) confirms that these constructs are distinct yet meaningfully related within the model. The results in

Table 4
Discriminant validity- HTMT.

	ATT	EE	FC	PE	PFR	PSR	PU	SI
ATT								
EE	0.622							
FC	0.583	0.799						
PE	0.579	0.771	0.817					
PFR	0.076	0.162	0.248	0.203				
PSR	0.111	0.22	0.275	0.226	0.894			
PU	0.497	0.682	0.599	0.747	0.114	0.181		
SI	0.491	0.639	0.687	0.657	0.255	0.242	0.431	

Table 4 demonstrate that the constructs in the model exhibit strong discriminant validity, with no HTMT values approaching or exceeding the critical thresholds of 0.85 or 0.90. These findings reinforce the measurement model's integrity, ensuring that each construct represents a unique theoretical concept. This rigorous assessment of discriminant validity enhances the model's credibility for subsequent analyses.

4.4. Evaluation of structural model

The analysis of hypothesized relationships in the study involves evaluating path coefficients, standard deviations (SD), p-values, R^2, f^2, and Q^2 values to assess the strength, direction, and significance of each hypothesis. These metrics collectively offer insights into the structural model's validity and explanatory power. H1 posits that PE influences ATT with a path coefficient of 0.671, a standard deviation of 0.073, and a p-value of 0.042. The hypothesis is accepted as the relationship is significant at the 5 % level. The model explains 36.7 % of the variance in ATT for this relationship, and the f^2 value of 0.17 indicates a medium effect size (Cohen, 1988). The Q^2 value of 0.234 confirms predictive relevance. H2 examines the impact of EE on ATT, showing a high path coefficient of 2.915, a low SD of 0.046, and a highly significant p-value of 0.002. The hypothesis is accepted, highlighting EE's strong positive effect on ATT. The f^2 value of 0.22 suggests a strong effect. H3 and H4 test the influence of SI and FC on ATT, respectively. Both hypotheses are supported with significant p-values (0.039 for both) and path coefficients of 1.770 SI and 1.763 FC. Their respective f^2 values, 0.19 and 0.18, indicate moderate effects, reinforcing their importance in shaping ATT. H5 and H6 focus on the roles of PSR and PFR on ATT. Both relationships are significant, with path coefficients of 0.250 and 0.429 and p-values of 0.048 and 0.041, respectively. However, the smaller f^2 values (0.11 and 0.12) suggest smaller yet meaningful contributions to explaining variance in ATT.

The model's R^2 and Q^2 values suggest an adequate level of explanatory power and predictive relevance across most relationships. These findings from

4.5. Evaluation of structural model

Table 5 collectively underscore the complexity of factors influencing attitudes and provide valuable insights into the interplay between various constructs [126]. Furthermore, we extended our prediction technique following the guidelines of Shmueli et al. [127], which yielded large predictive relevance (i.e., PLS-SEM_MAE < LM_MAE for all items of Attitude) (refer to Table 6). So, the study offers empirical support for the proposed structural relationships, with implications for designing interventions and strategies in the relevant domain.

4.5.1. Moderating effects

The moderation analysis was conducted using a two-stage approach, as recommended by Becker et al. [128]. H7 hypothesizes an indirect effect of PU on PE on ATT. The path coefficient (−0.795) is not significant ($p = 0.215$), leading to rejection. The negative coefficient suggests that the hypothesized relationship is not well-supported empirically. H8 and H9 test PU's indirect effects on EE and SI, respectively, influencing ATT. H8 is accepted with a positive path coefficient of 1.450 and a significant p-value (0.044), indicating that PU positively moderates EE's influence on ATT. H9, while accepted, presents an intriguing finding; the negative path coefficient of −2.667 with a highly significant p-value (0.004) suggests that PU inversely affects SI's impact on ATT. Finally, H10 evaluates PU's indirect impact through FC on ATT. With a path coefficient of 1.264 and an insignificant p-value (0.101), this hypothesis is rejected, underscoring that PU's moderating role is not empirically supported in this context. Furthermore, Dawson [129] provided more evidence that the significant result was proven by an interaction plot (refer to Figs. 2 and 3).

Table 6
Results of PLSpredict.

Endogenous variable	Q^2predict	PLS-SEM_MAE	LM_MAE
ATT1	0.046	0.426	0.457
ATT2	0.178	0.439	0.490
ATT3	0.282	0.470	0.515
ATT4	0.121	0.493	0.541

5. Discussion and implications

5.1. Discussion

The hypothesis analysis provides critical insights into the factors influencing attitudes (ATT) in the study. The findings align with existing literature while also offering unique contributions to the field of behavioral research and decision-making.

5.1.1. Performance expectancy (PE)

Performance expectancy (PE) significantly influences ATT, as indicated by a strong path coefficient and a p-value. This finding corroborates prior studies that highlight performance expectancy as a critical determinant of technology acceptance and behavior formation [40]. Recent research (e.g., [130,131] further reinforces this relationship, suggesting that users' perceptions of improved performance drive positive attitudes toward technology adoption. This aligns with our results, indicating that individuals' expectations of improved efficiency and outcomes in using FinTech services are essential in shaping favorable attitudes. Our findings also reflect the growing recognition that technology users increasingly prioritize functional and utilitarian benefits when making adoption decisions [132]. Thus, this reinforces the role of utility perception in behavioral models, particularly in the context of FinTech.

Table 5
Structural model evaluation.

Hypothesis	Hypothesized Relationships	Path coefficients	SD	P-Values	Decision	R^2	f^2	Q^2
H1	PE -> ATT	0.671	0.073	0.042	Accepted	0.367	0.17	0.234
H2	EE -> ATT	2.915	0.046	0.002	Accepted		0.22	
H3	SI -> ATT	1.770	0.074	0.039	Accepted		0.19	
H4	FC -> ATT	1.763	0.061	0.039	Accepted		0.18	
H5	PSR -> ATT	0.250	0.059	0.048	Accepted		0.11	
H6	PFR -> ATT	0.429	0.045	0.041	Accepted		0.12	
H7	PU-> PE -> ATT	−0.795	0.088	0.215	Rejected			
H8	PU-> EE -> ATT	1.450	0.120	0.044	Accepted			
H9	PU-> SI -> ATT	−2.667	0.087	0.004	Accepted			
H10	PU-> FC -> ATT	1.264	0.091	0.101	Rejected			

ATT=Attitude, EE=Effort Expectancy, FC=Facilitating Condition, PE=Performance Expectancy.
PFR=Perceived Financial Risk, PSR=Perceived Security Risk, PU=Perceived Usefulness, SD=Standard Deviation.

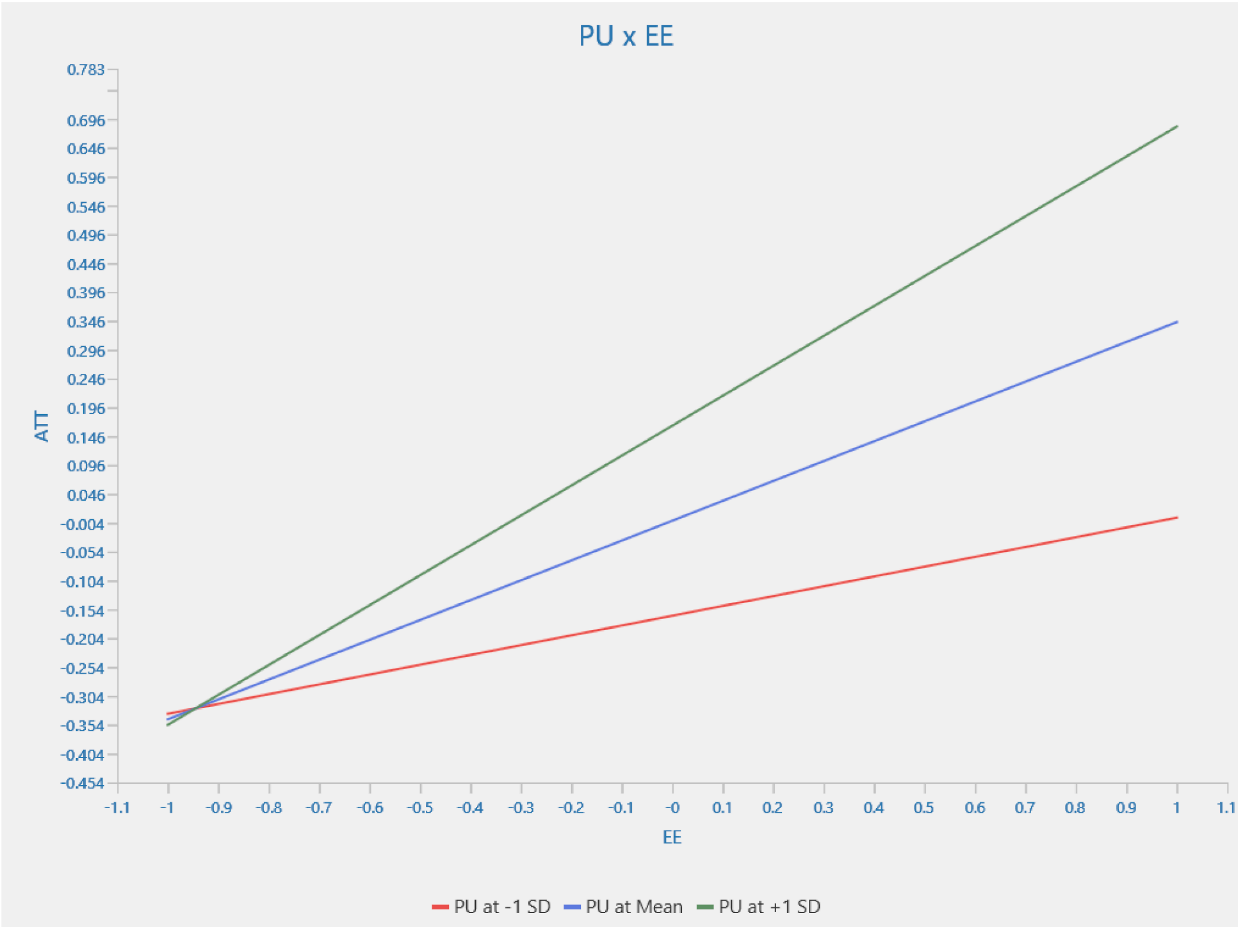

Fig. 2. Simple Slope Analysis: EE*Perceived Usefulness (PU) Interaction Plot.

5.1.2. *Effort expectancy (EE)*

Effort expectancy (EE) exhibits the highest positive influence on ATT, with a robust path coefficient and a significant p-value. This outcome aligns with earlier studies by Davis et al. [14] and more recent findings [133,134], which emphasize the significance of ease of use in shaping attitudes. The strong impact of EE may reflect the critical importance of reducing cognitive and operational barriers for users, making the technology easier to use and thereby fostering positive attitudes [135]. Our results confirm the dominant role of effort expectancy in determining user acceptance, a notion that has been continually reinforced in the literature [37]. The fact that EE exhibits the highest effect suggests that FinTech services, which are often perceived as complex, benefit from simplifying user interfaces and processes to improve user experience and overall adoption.

5.1.3. *Social influence (SI) and facilitating conditions (FC)*

Social influence (SI) and facilitating conditions (FC) also emerge as critical predictors of ATT, with significant path coefficients and p-values. These findings are consistent with the UTAUT model [37], which underscores the importance of social norms and environmental support in influencing attitudes. However, the moderate f^2 values suggest that while these constructs are influential, their effects are less pronounced than those of effort expectancy. Recent studies by Oliveira et al. [136, 137] demonstrate that social influence remains a strong determinant of technology adoption in the FinTech sector, but its impact diminishes in the presence of more personal drivers, such as perceived ease of use and usefulness. This highlights the evolving nature of consumer decision-making, where social factors become less important as individuals gain experience with the technology.

5.1.4. *Perceived security risk (PSR) and perceived financial risk (PFR)*

Perceived security risk (PSR) and perceived financial risk (PFR) have weaker but statistically significant impacts on ATT. This finding is consistent with research on risk perception, which indicates that individuals weigh potential losses against anticipated benefits [138]. Recent studies (e.g., [58,108]) have confirmed that while security concerns are important, they are often secondary to functional considerations such as ease of use and performance expectancy in the FinTech sector. The nuanced role of perceived risks in decision-making underscores the need for risk mitigation strategies, such as enhancing trust in digital platforms and offering robust security measures to alleviate concerns and improve attitudes toward FinTech services [139].

5.1.5. *Moderating effects of Perceived Usefulness (PU)*

The rejection of H7, which proposed PU's indirect effect through PE on ATT, suggests that the direct relationship between PU and PE does not significantly translate into attitude formation. This contrasts with prior studies [14,37], which often demonstrate the mediating role of performance expectancy. Our findings, however, could be explained by domain-specific factors; for instance, the emphasis on performance-related benefits may not be as potent when individuals already perceive FinTech services to be useful. Moreover, recent research (e.g., [140,141]) indicates that while PU is essential in some contexts, its effect may not always serve as a mediating factor, particularly in technologies like FinTech where ease of use (EE) plays a more dominant role in influencing attitudes.

PU positively moderates the relationship between Effort Expectancy (EE) and Attitude (ATT), supporting the notion that individuals' perceptions of usefulness amplify the impact of ease of use on attitudes

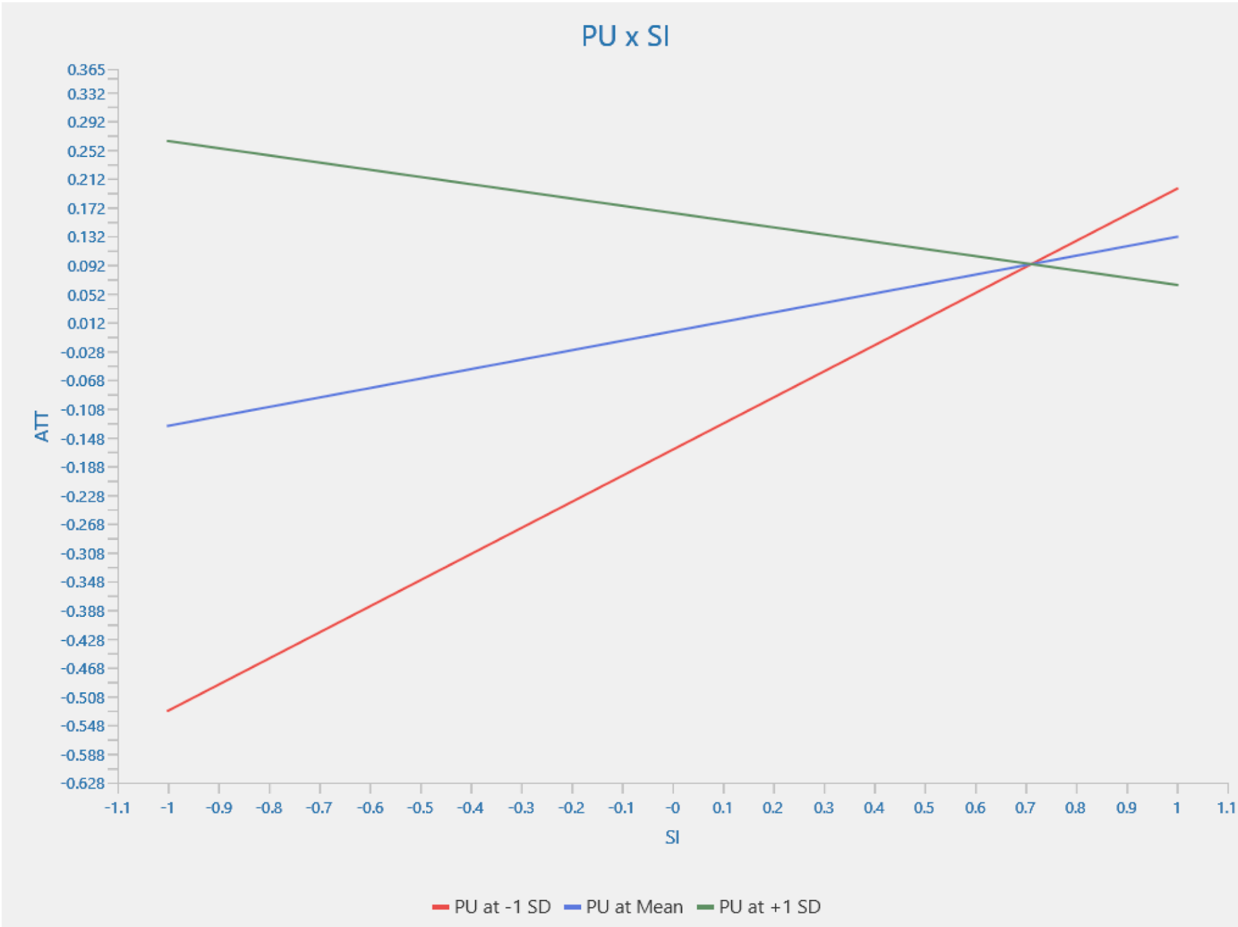

Fig. 3. Simple Slope Analysis: SI*Perceived Usefulness (PU) Interaction Plot.

[40]. This finding aligns with recent studies by Sair & Danish [142] and Wu & Chen [105], who highlight that perceived usefulness enhances the impact of effort expectancy on adoption, especially in contexts where users expect technology to deliver both functional benefits and ease of use.

In contrast, H9 shows a negative moderating effect of PU on the relationship between SI and ATT. This intriguing result suggests that as the perceived utility of FinTech services increases, the influence of social norms (SI) diminishes, a pattern also observed in the work of [143]. This aligns with the growing body of literature indicating that utility considerations often outweigh social influences as perceived usefulness becomes more prominent in decision-making [144]. It implies that when users see clear benefits in using a technology, they are less likely to be swayed by social pressures.

Finally, the rejection of H10, which proposed PU's indirect effect through FC on ATT, suggests that PU does not significantly enhance the influence of FC on ATT. This finding contrasts with studies emphasizing the interactive role of PU in resource-based support systems [37]. A possible explanation could be the high baseline influence of facilitating conditions, such as accessibility and infrastructure, which already play a significant role in shaping attitudes toward FinTech adoption [34,103]. Once these basic facilitating conditions are met, the incremental impact of PU may be minimal, reducing the potential for PU to further moderate this relationship.

5.2. Theoretical implications

This study contributes to the theoretical advancement of FinTech adoption research by providing insights into the role of consumers' attitudes toward FinTech innovation and the moderating effect of perceived usefulness. Grounded in the UTAUT and Perceived Risk theory, our research extends the existing frameworks by highlighting the dual significance of individuals' attitudes. Moreover, to enhance the comprehensiveness of the analysis of Bangladeshi consumers' banking behaviour, we incorporate PFR and PSR in our model as independent variables, evaluating their direct influence on customers' attitudes toward FinTech innovation. Since both the PFR & PSR have a significant negative impact on attitude, they challenge the assumptions of traditional risk-averse models and highlight the necessity for a deeper exploration of how cultural and socio-economic factors shape psychological perceptions and decision-making processes in emerging markets. Besides, our study developed and evaluated a moderated mechanism by incorporating perceived utility as a moderating variable. It provides a nuanced understanding of the conditions under which consumer attitudes translate into adoption behaviour, making it a pivotal factor in studying innovative financial technology. Our research findings contradict the presumption that PU consistently moderates or enhances the influence of PE and FC on attitudes, offering a more context-specific comprehension of consumer behavior. From a theoretical standpoint, this finding massively contributes to the literature and calls for further exploration of different variables in the adoption process across diverse technological domains.

5.3. Practical implications

This study's findings provide critical insights for financial service providers, FinTech developers, policymakers, and marketing strategists to enhance the adoption of FinTech technologies, particularly in developing countries like Bangladesh. By understanding customer attitudes and the moderating influence of perceived usefulness (PU), firms can design products and services that better align with user preferences, ensuring that they are user-friendly and more widely accepted. Our study not only strengthens the theoretical foundation but also offers practical guidance for FinTech providers to develop tailored interventions that improve perceived usefulness, thus promoting increased adoption rates.

5.3.1. Implications for FinTech providers

FinTech companies can leverage the insights from this study to create more personalized customer experiences, increasing both adoption and retention. By focusing on enhancing the perceived utility of their services whether through clear demonstrations of the practical benefits or simplifying complex processes, FinTech firms can better meet the needs of users. As our findings suggest, increasing ease of use (effort expectancy) and addressing the functionality of services (performance expectancy) are crucial in shaping user attitudes. Moreover, incorporating user feedback into the product development process is vital for continuous improvement. Customization and user-centric designs could further strengthen the adoption of FinTech solutions. Additionally, offering incentives and demonstrating the utility of FinTech services through real-world applications will help ease potential users' concerns. In emerging markets like Bangladesh, where FinTech adoption is still in the early stages, FinTech companies should prioritize initiatives that increase financial literacy. These initiatives can educate potential users about the advantages of FinTech services, addressing misconceptions and mitigating resistance to adopting new technologies. By enhancing consumer awareness of the benefits, especially in regions where digital financial services are underutilized, FinTech firms can foster trust and encourage adoption.

5.3.2. Implications for policymakers and regulators

From a policy perspective, regulators can use the findings from this study to shape regulations that promote the growth of FinTech solutions while protecting users. In Bangladesh and similar markets, regulatory authorities can take a proactive approach to establishing clear guidelines on data privacy, security, and consumer protection. By doing so, policymakers can address concerns related to perceived risks, particularly security and financial risks, which were identified as critical determinants of user attitudes. Developing frameworks that ensure the safety and transparency of FinTech services will foster trust among users and improve adoption rates. Additionally, policymakers should collaborate with financial institutions, technology developers, and education providers to create a supportive ecosystem for FinTech innovation. They can promote the development of infrastructure that supports both access to and ease of use of digital financial services.

5.3.3. Implications for other countries and regions

While this study provides valuable insights into the context of Bangladesh, its implications extend beyond the country and can be applied to other developing regions and countries with similar socio-economic and technological landscapes. In countries with nascent FinTech markets, the adoption challenges identified in this study, such as perceptions of ease of use, performance expectancy, and security risks, are likely to be common. Therefore, the practical recommendations outlined here enhancing perceived usefulness, simplifying technology, and increasing financial literacy apply to other regions aiming to increase FinTech adoption. For instance, in African countries, where mobile money services have seen rapid growth, similar strategies for enhancing user experience and addressing security concerns have been found to improve adoption [3]. Similarly, in other South Asian nations like India and Sri Lanka, where mobile banking and digital wallets are gaining momentum, addressing user concerns about the perceived risks and highlighting the utility of FinTech services could significantly boost their acceptance [145]. Policymakers in different regions can adapt the study's findings to local contexts, ensuring that policies are tailored to each country's specific cultural, economic, and technological environments. For example, in regions with lower levels of internet penetration, policies could focus on improving digital infrastructure and facilitating broader access to mobile networks, ensuring that FinTech solutions are accessible to a larger portion of the population.

6. Limitations

This study has several limitations that should be considered when interpreting the findings. Firstly, the use of convenience sampling may limit the generalizability of the results, as the sample may not represent the broader population of FinTech users in Bangladesh or other regions. The respondents were predominantly individuals who are already familiar with digital technologies, which may introduce bias and overlook the perspectives of those with limited access to or experience with FinTech services. Additionally, the study employed a cross-sectional design, providing a snapshot of user attitudes at a single point in time. This design does not capture long-term behavior or shifts in attitudes, which could evolve as users gain more experience with FinTech platforms. Moreover, the reliance on self-reported data through surveys could result in response bias, where respondents may present socially desirable answers instead of reflecting their true attitudes or behaviors. Lastly, the study primarily focused on individual-level factors, without accounting for macro-level influences such as government regulations, infrastructure, or socio-economic factors, which also play a significant role in FinTech adoption.

7. Future research directions

Future research should address the limitations of this study by adopting a longitudinal design to explore how FinTech adoption and attitudes evolve. This would allow researchers to track changes in user behavior and perceptions as they gain more experience with the technology. Furthermore, future studies could use a more diverse sampling method, such as random or stratified sampling, to ensure that the findings are more representative of the general population. Cross-cultural research across different countries or regions would also be valuable to identify both universal and context-specific factors that influence FinTech adoption. Additionally, incorporating objective behavioral data, such as actual usage or transaction records, alongside self-reported data, could improve the accuracy of the findings. Future studies should also examine the role of external factors, such as government policies and digital infrastructure, in shaping user attitudes toward FinTech, as these factors can significantly impact adoption. Finally, research could explore the impact of financial literacy and trust-building measures, such as user education programs and regulatory frameworks, on FinTech adoption, particularly in developing economies [26].

8. Conclusion

To summarise, this empirical research, utilising the lens of the UTAUT and Perceived Risk Theory, explored consumers' attitudes toward FinTech innovation and examined the moderating role of perceived usefulness (PU) in shaping these attitudes. Moreover, this study seeks the direct impact of PE, EE, FC, SI, PFR, and PSR on the attitudes of the users. The findings indicate that consumer attitudes are shaped by a combination of positive and negative influences from key factors, including PE, EE, FC, SI, PFR, and PSR. These research findings also suggest that while PU is crucial in directly shaping attitudes, its moderating role may not always extend to the relationships between PE, FC, and attitude, particularly in developing economies where practical considerations often take precedence over perceived usefulness. Besides, researchers found a substantial moderating effect of PU in relationship with the variables EE and SI towards attitude. FinTech innovation, a rapidly growing sector that is transforming financial services globally. Research into this sector holds immense significance for developing economies, where FinTech innovations possess the potential to enhance financial inclusion and accessibility. However, their adoption may encounter resistance stemming from cultural, financial, and security concerns.

CRediT authorship contribution statement

Mohammad Abdullah Al Mamun: Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization. **Tipon Tanchangya:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Formal analysis, Data curation, Conceptualization. **Md Abidur Rahman:** Writing – review & editing, Writing – original draft, Data curation. **Md. Mehedi Hasan:** Writing – review & editing, Writing – original draft, Resources, Project administration, Methodology, Investigation. **Naimul Islam:** Writing – review & editing, Writing – original draft, Resources, Investigation, Formal analysis. **Bony Yeamin:** Writing – review & editing, Writing – original draft, Investigation, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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