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Exploring Factors Influencing Behavioral Intention to Use Chatbot Services in the Banking Industry of Bangladesh

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ABSTRACT

Information technology has transformed the global economy, particularly the financial sector, by using different industry 4.0 technologies, such as big data analytics, the Internet of Things (IoT), and Artificial Intelligence (AI). Nowadays, customers use AI-based chatbots to check account balances, interact quickly, make disbursements, and manage the money they have with banks or other financial institutions. This study aims to evaluate the factors influencing customers' chatbot adoption intention in their banking activities in Bangladesh. The measurement development and hypotheses are based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) framework, extended with two external factors (i.e., customers' perceived privacy risk and awareness of service). This study adopts a quantitative approach for data collection using an online survey. A total of 324 responses were collected from the actual bank chatbot users and evaluated using Structural Equation Modeling (SEM). The findings demonstrate that performance expectancy, effort expectancy, and perceived privacy risk had an impact on customers' willingness to use banks' chatbot services. Awareness of service has a strong, favorable impact on performance expectancy and effort expectancy. The findings also provide key recommendations for financial service providers on how to boost their customers' intention to continue using chatbot services, supporting sustainable and long-term digital growth.

KEYWORDS: Chatbots, Behavioral Intention, UTAUT2, Banking Sector, Technology Adoption

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1. Introduction

Nowadays, digital innovations such as chatbots, online transaction systems, peer-to-peer credit, automated financial advising, and blockchain technologies have significantly transformed the domain of financial services (Wu, 2023). A primary shift is reflected in the ways financial organizations offer products and services to customers. Among these innovations, chatbots (chat robots) have emerged as a key development in reshaping the financial landscape over the last decade. Chatbots are computerized services designed to simulate human-like conversations through text or voice interactions (Chiu et al., 2024; Sharda et al., 2020). Generally, they offer instant support to users by answering queries, sharing information, performing tasks, and automating routine interactions. These chatbots can also aggregate a large volume of data regarding customer profiles and transactional histories to support efficient decision-making. Besides, chatbots, integrated with complementary technologies (i.e., big data analytics, Internet of Things (IoT), and Artificial Intelligence (AI)), can highly improve operational efficiency (Al Nasseri et al., 2015). Therefore, in recent years, financial organizations have started to incorporate chatbot services into their daily operations. Studies also highlight the different benefits of using chatbots. For instance, chatbots facilitate precise, data-driven customer engagement and provide 24/7 automated inquiry handling, thereby reducing labor costs while maintaining consistent service delivery (Nguyen et al., 2021; Suhel et al., 2020; Richad et al., 2019; Vieira & Sehgal, 2018). Similarly, chatbots personalize services, boost customer satisfaction, detect fraudulent activities, and improve the overall operational performance of financial organizations (Alt et al., 2021).

Realizing chatbots' growing impact in different industries, it is projected that the global chatbot market will attain a market valuation of 20.81 billion USD by 2029 (Mordor Intelligence, 2024). Several studies have been conducted to evaluate customers' intentions to use chatbots across various settings, such as entertainment (Lee & Choi, 2017; Zarouali et al., 2018), e-commerce (Ikumoro & Jawad, 2019), insurance (Cardona et al., 2019), healthcare (Laumer et al., 2019; Prakash & Das, 2020), customer support (Ashfaq et al., 2020), shopping (Kasilingam, 2020), travel and tourism (Melián-González et al., 2021), and higher education institutions (Mohd Rahim et al., 2022). However, in the financial sector, studies have primarily focused on insurance, e-commerce, and banking (Wube et al., 2022), with comparatively limited attention given to the banking industry.

Many scopes exist in the banking sector where studies can concentrate (Richad et al., 2019). Some studies focus on use or actual use of the chatbot in their banking activities (Gupta & Sharma, 2019), customer satisfaction regarding the use of chatbot (Qureshi et al., 2024), propensity of customers to engage with chatbots (Abdul Karim Shaikh et al., 2023) or the significance of usage of chatbot (Quah & Chua, 2019). Recently, several Bangladeshi banks such as BRAC Bank, City Bank, and Eastern Bank, have begun implementing chatbot services to assist customers with routine tasks including account balance inquiries, loan product information, transaction alerts, and service requests via websites and messaging platforms.

However, chatbots' deployment remains limited in scope, often lacking personalization, multilingual support, and integration with core banking systems. Despite their growing presence and importance, very few studies have focused on the Bangladeshi context. Majority of the studies focus on chatbot adoption in developed countries, overlooking the technological and economic dynamics unique to Bangladesh. Thus, there is a clear need for empirical research to support more effective adoption and utilization of this technology in Bangladesh. Alt et al. (2021) also emphasize the importance of identifying the drivers of chatbot adoption to ensure that both banking institutions and their customers can fully realize its benefits. Additionally, research mostly focused on the use or actual use of chatbot by using Technology Acceptance Model (TAM) model (Hasan et al., 2023; Nguyen et al., 2021; Richad et al., 2019). Notably, no study to date has applied the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model to examine chatbot adoption intention in Bangladeshi banks. To address this gap, the present study employs the UTAUT2 model to the setting of Bangladesh to examine factors influencing the intention to adopt chatbots in banks.

Therefore, the objective of this study is to explore and analyze factors influencing customers' adoption intention of banking chatbots in Bangladesh. The following research questions guide the study:

RQ1: What are the key factors influencing the customers' behavioral intention to adopt banking chatbots in Bangladesh?

RQ1: How do these factors impact the customers' behavioral intention to adopt banking chatbots?

In this study, the researchers conducted a survey among banking customers in Bangladesh. The research is grounded in the UTAUT2 model, extended with two external variables: perceived privacy risk and awareness of service. The findings reveal that performance expectancy and effort expectancy are major drivers of chatbot adoption in Bangladeshi banking, while privacy concerns remain a barrier despite increased awareness. Therefore, this study offers practical insights for banking service providers, chatbot developers and policymakers to better understand customer responses to chatbots and develop effective strategies to promote sustained chatbot adoption, ultimately supporting the long-term growth of the banking sector.

This paper is organized as follows: the next sections present a review of relevant literature and the theoretical framework. Subsequently, the research methodology, results, and discussion are presented. Practical implications are then outlined, along with the study's limitations and future research directions. The paper ends with final remarks.

2. Literature Review

2.1 Chatbot Services

Since artificial intelligence (AI) performs human-like cognitive functions such as perception, sensory data processing, and knowledge acquisition (Gams et al., 2019), it is now employed in a variety of capacities (Svenningsson & Faraon, 2019). In this context, Følstad & Brandtzaeg

(2017) highlight the growing need for innovative AI-powered chatbots for digital transformation across various sectors. A chatbot is an artificial intelligence-based computer software which helps to continue conversations with people using apps or websites (Lui & Lamb, 2018). These conversations can be text-based or spoken without any time or space constraints. The chatbot's primary functions include assisting users with information searches, answering questions, and developing social interactions. Therefore, organizations are starting to integrate chatbots into their daily operations to enhance corporate expansion and customer service (Chung et al., 2020), a strategy that hinges on the broad acceptance of customers to attain favorable outcomes (Ramachandran, 2019). Despite the growing interest in chatbots, many companies remain uncertain about whether the benefits of investing in this technology outweigh the costs of hiring people for reliable customer service (Barba-Sánchez et al., 2007). The substantial financial and operational commitments required for AI adoption have led businesses to critically assess its strategic implications before full-scale implementation (Nili et al., 2019).

2.2 Chatbot Services in the Financial Industry

Nowadays, AI has become a common and frequently used technology in the financial industry. It improves operational excellency by reducing fraud, managing risks, and taking better decisions. Similarly, chatbots services are used in this industry to enhance client interactions and resolve issues and to investigate some factors like the security flaws, implementation, adoption goals, attitudes, perception, trust, and engagement of chatbot (Wube et al., 2022). A growing body of literature has examined the use of chatbot services in the financial sector (Sugumar & Chandra, 2021a; Wube et al., 2022). For example, Sugumar & Chandra (2021) explore the factors influencing the users' acceptance of chatbots within financial services across India, the United States, and Singapore. They employ the UTAUT2 and BDI frameworks for their study. Their findings highlight that human-like quality is important to influence customer adoption, and consumer preferences blur the distinction between artificial entities and people. De Andrés-Sánchez & Gené-Albesa (2023) also find important factors that affect users' acceptance of conversational bots in the insurance sector. They reveal considerable resistance to chatbot technology using the UTAUT framework. Their results also highlight that social influence, effort expectancy, and trust are the most important elements for getting users' acceptance.

These studies depict the possible pros and cons of using chatbots in the financial industry. However, more diverse research is needed for a deep understanding of user behavior to adopt chatbot technology within this industry.

2.3 Chatbot Services in the Banking Sector

The banking sector is an active adopter of chatbot technology within the financial industry. Recent studies highlight that banks are adopting chatbot services to enhance data processing, analytical, and customer service efficiency (Alt et al., 2021; Hasan et al., 2023). AI-powered chatbots enable real-time communication, interacting with bank customers in natural language, either through text or voice. A large amount of empirical research has investigated the adoption of banking chatbots across diverse national contexts. These studies examine banking users' behavior and acceptance patterns toward chatbots using various theoretical models and related contextual variables. For example, Alt et al. (2021) use the extended TAM framework to study how Romanian banks' customers are adopting chatbots. Researchers in India have used numerous methods to study how chatbots are used in Indian banks. Trivedi (2019) employs the Information System Success Model, Abdul Karim Shaikh et al. (2023) use the TAM framework, and Gupta & Sharma (2019) adopt an exploratory approach grounded in customer attitudes and perceptions. Similarly, Quah & Chua (2019) conducted a study in Singapore, and Richard et al. (2019) investigated chatbot adoption among Millennials using the TAM framework in Indonesia. Nguyen et al. (2021) also investigate the context of Vietnam and highlight the importance of contentment, trust, and perceived usefulness in persistent use of banking chatbots.

These studies provide a deep insight into the diverse factors that shape customers' adoption behaviors toward banking chatbots. However, these studies in the banking sector are still limited compared to the insurance and e-commerce sectors within the financial industry (Wube et al., 2022). Besides, very few studies have concentrated on the context of Bangladesh. For instance, Hasan et al. (2023) employ the extended TAM framework to study the customers' banking chatbot adoption behavior. To date, no prior study has applied the UTAUT2 framework in this context. Thus, this study employs UTAUT2 framework with two external factors perceived privacy risk and awareness of service to address the research gap. This framework will provide a deeper understanding of customers' chatbot adoption behavior in Bangladeshi banks.

3. Conceptual Framework and Hypotheses Development

A large number of theories, including the Theory of Reasoned Action, the Diffusion of Innovation Theory, the Theory of Planned Behavior (TPB), the Decomposed Theory of Planned Behavior, TAM, the Extended TAM, and UTAUT, are developed and applied to investigate users' technology adoption behavior within Information Systems (IS) discipline (Hanafizadeh & Khedmatgozar, 2012). The UTAUT framework has gained popularity among these theories for its robust explanatory power (Ajzen, 1991; Davis, 1989). It has consolidated key constructs from earlier models and become a framework of reference for many digital technologies both inside and outside of organizational settings (Sugumar & Chandra, 2021). Venkatesh et al. (2012) introduce a new version of this framework 'UTAUT2' to examine consumer technology acceptability and adoption more explicitly. Later, UTAUT2 becomes one of the mostly cited models within IS literature. Recently, UTAUT and its extensions are being used in studies (e.g., Emon et al., 2023) in examining behavioral intention to adopt and use AI related technologies.

Therefore, this study employs the UTAUT2 framework to address the research questions. Reviewing previous studies of the UTAUT2 in the context of the banking sector, this study adopts constructs highly relevant to the adoption of banking chatbots. The proposed conceptual model (Figure 1) incorporates four basic constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Behavioral Intention to Use Banking Chatbots (BI). This model also adapts two external variables: Perceived Privacy Risk (PPR) and Awareness of Service (AW) from the work of Alt et al. (2021) to increase its contextual relevance. While Alt et al. (2021) extended the basic TAM with PPR and AW, the present study integrates these same extensions within the UTAUT2 structure. This approach enables the model to address both cognitive and contextual factors related to the adoption of banking chatbots in Bangladesh.

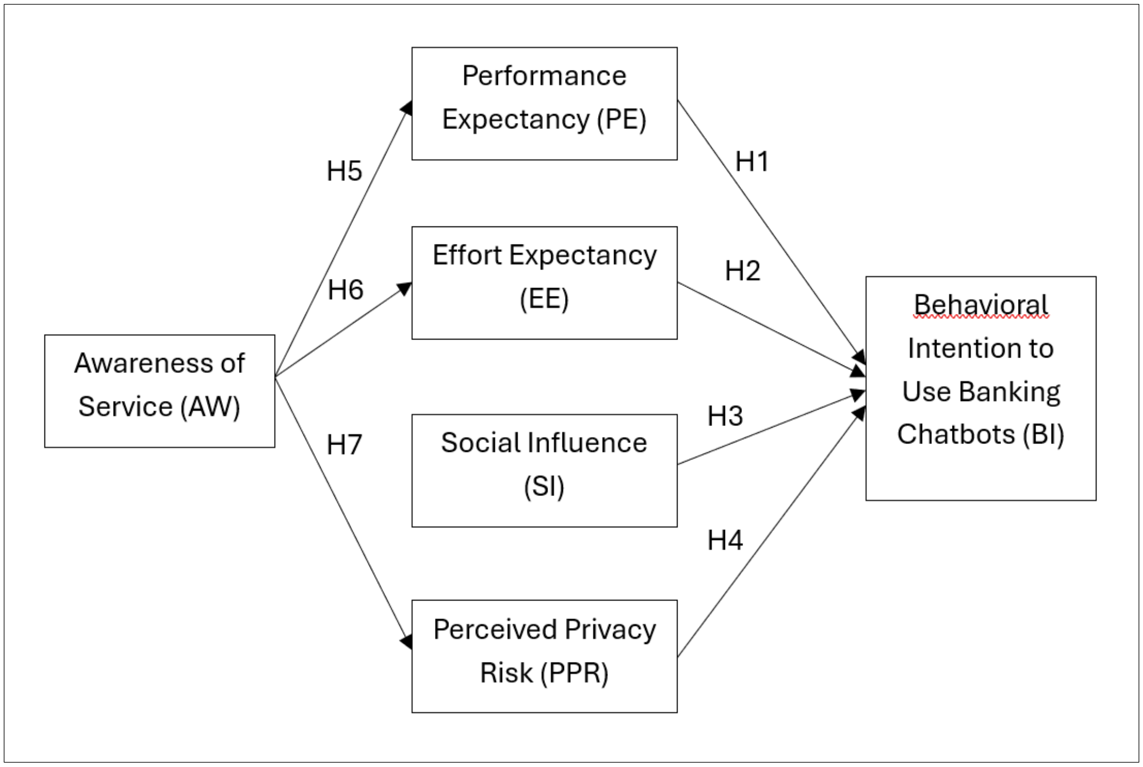

Figure 1: Proposed Conceptual Model

3.1 Behavioral Intention to Use Banking Chatbot (BI)

Behavioral intention is defined as a reliable indicator of an individual's willingness to engage in a certain activity and serves as a strong predictor of actual usage (Alkhowaiter, 2022; Venkatesh et al., 2003). Within the academic literature on digital banking adoption, performance expectancy or perceived usefulness (Alalwan et al., 2018; Farah et al., 2018; Koenig-Lewis et al., 2010; Martins et al., 2014; Safeena et al., 2012), effort expectancy or perceived ease of use (Alalwan et al., 2018; Farah et al., 2018; Martins et al., 2014; Safeena et al., 2012), perceived privacy risk (Akturan & Tezcan, 2012; Arif et al., 2016; Giovanis et al., 2012; Shankar & Kumari, 2016)), awareness of the service (Al-Somali et al., 2009; Pikkarainen et al., 2004; Sathye, 1999), and social influence (Emon et al., 2023; Sugumar & Chandra, 2021), were identified as significant predictors of behavioral intention. As noted by Sugumar & Chandra (2021), when a technology such as banking chatbots is still in its early stages of implementation, actual usage behavior can be difficult to assess. This challenge is particularly relevant in Bangladesh, where chatbot services are relatively new and unfamiliar to many banking customers. In such cases, behavioral intention serves as a meaningful proxy for predicting future adoption. Accordingly, this study aims to examine customers' behavioral intentions toward using banking chatbot services by drawing on these theoretically and empirically supported predictors.

3.2 Performance Expectancy (PE)

Performance expectancy is defined as the extent to which an individual perceives that utilizing the systems would enhance their job performance (Venkatesh et al., 2003). This construct closely parallels the perceived usefulness of the TAM model, as further conceptualized within the UTAUT by Li & Kishore (2006). Across a range of financial technology studies, including mobile banking, online banking, and mobile payment, performance expectancy has consistently emerged as a robust predictor of users' behavioral intentions. For instance, Richad et al. (2019) identify a significant influence of perceived usefulness on users' willingness to adopt banking chatbots. In this context, performance expectancy centers on customers' beliefs about the extent to which chatbot services can help them efficiently manage banking-related tasks (Sugumar & Chandra, 2021). For this reason, the initial hypothesis is put forth:

H1: Performance expectancy has a significant and positive effect on users' intention to use the banking chatbot.

3.3 Effort Expectancy (EE)

Effort expectancy is a significant factor that affects the chances that people would embrace and use a certain technology. This idea is how people think the system is easy to use and how they rate its overall functionality (Venkatesh et al., 2003). Studies have employed effort expectation in different technology settings, such as mobile payments (Tak & Panwar, 2017) and online banking (Arenas-Gaitán et al., 2015). The perceived ease of use from the TAM model and the effort expectation from the UTAUT model are equivalently used in literature (Li & Kishore, 2006). Effort expectancy has been established as a reliable indicator of someone's intention to use financial technologies like mobile banking, online banking, and mobile payments in several research investigations. Richad et al. (2019) state that the perceived ease of use affects behavioral intention to use the banking chatbot. They reveal that chatbots' effort expectation is highly dependent on customers' perception of using the software easily to get the required information with little effort. For instance, an automated conversational agent on a bank's website may answer queries about services on its own, which would improve the overall user experience (Richad et al., 2019). So, the second hypothesis is:

H2: Effort expectancy has a significant and positive effect on users' intention to use the banking chatbot.

3.4 Social influence (SI)

Social influence is the extent to which a person believes that significant others believe he or she should utilize the new system (Venkatesh et al., 2003). It plays a key role in the acceptance and implementation of various emerging technologies, such as online gaming (Xu, 2014), mobile applications (Tak & Panwar, 2017), and mobile payments (Morosan & DeFranco, 2016). Sugumar & Chandra (2021) indicate that social influence is very important for customers to start using chatbots for banking and financial services. People often seek validation and encouragement from trusted peers and acquaintances when deciding to engage with new digital solutions, especially those perceived to involve financial risk. Recent studies also show that social influence has a big impact on how likely customers are to use new technology (Sobti, 2019). So, the third hypothesis is made:

H3: Social influence has a significant and positive effect on users' intention to use a banking chatbot.

3.5 Perceived Privacy Risk (PPR)

Customers in the banking sector often have big worries about how safe and private their personal financial information is. One common concern is that financial institutions will share personal information with third parties without permission (Kolodinsky et al., 2004). This anxiety, which is often conceptualized as a perceived privacy risk, is caused by people's fear of losing control over their private information, especially when it is accessed or used without their permission (Akturan & Tezcan, 2012). Past studies on the adoption of digital banking have shown that perceived risk is often a barrier to the widespread acceptance of online financial services (Giovanis et al., 2012). For example, Arif et al. (2016) and Shankar and Kumari (2016) reveal that perceived privacy risk has a significant negative influence on customers' attitudes toward mobile banking and their intention to use these services. Thus, the fourth hypothesis is suggested:

H4: Perceived privacy risk has a negative effect on users' intention to use a banking chatbot.

3.6 Awareness of Service (AW)

Awareness of technological innovation is a critical adoption factor. Sathye (1999) states that customers' willingness to adopt any emerging digital tool largely depends on their familiarity with that product or service. Pikkarainen et al. (2004) also stress that customers' understanding of internet banking is a key factor in its acceptance. A lack of awareness can act as a substantial barrier to adoption, as reaffirmed by Sathye (1999), who identifies knowledge gaps as major inhibitors of digital banking uptake. On the other hand, greater awareness can reduce perceived risks (Hanafizadeh & Khedmatgozar, 2012) and positively influence perceived usefulness and perceived ease of use of digital banking services (Al-somali et al., 2009). Therefore, the desired hypotheses are as follows:

H5: Awareness of service has a significant and positive effect on perceived expectancy.

H6: Awareness of service has a significant and positive effect on effort expectancy.

H7: Awareness of service has a significant and negative effect on perceived privacy risk.

4. Methodology

4.1 Measurement instruments

The measurement items for latent constructs within the proposed model were adapted from previous literature to ensure the validity of all measures. A total of 21 items resulted and were used for the model. The detailed measurement items used to measure each construct, and their sources, are presented in Table 1.

Table 1: Summary of measurement items

Constructs	Measurement Items	Sources
Performance Expectancy (PE)	PE1: I find chatbots helpful for my banking endeavours. PE2: With the help of a chatbot, I can easily accomplish my goals. PE3: The chatbot speedily completes my banking tasks. PE4: The chatbot makes me more efficient	(Sugumar & Chandra, 2021; Venkatesh et al., 2003; Venkatesh et al., 2012)
Effort Expectancy (EE)	EE1: I think learning how to use banking chatbots is very easy. EE2: I can easily become an expert in using banking chatbots if I want. EE3: Banking chatbots are very easy to use.	(Sugumar & Chandra, 2021; Venkatesh et al., 2003; Venkatesh et al., 2012)
Social Influence (SI)	SI1: Chatbots are recommended by important individuals in my life. SI2: Individuals who shape my behaviour believe that I should adopt chatbots. SI3: Individuals whose opinions I respect desire that I employ chatbots.	(Sugumar & Chandra, 2021; Venkatesh et al., 2003; Venkatesh et al., 2012)
Perceived privacy risk (PPR)	PPR1: Using the banking chatbots could result in the misuse, improper sharing, or sale of private information. PPR2: The banking chatbot has the potential to intercept or access personal information. PPR3: Using a banking chatbot could result in the collection, tracking, and analysis of private information. PPR4: Employing the banking chatbot may disclose or provide access to private information.	(Alt et al., 2021; Yang et al., 2015)
Awareness of service (AW)	AW1: My bank has informed me of its policy on the use of banking chatbots. AW2: My bank has specific plan on how to use banking chatbot. AW3: My bank has provided me with enough information about how to use the banking chatbot.	(Alt et al., 2021)

Constructs	Measurement Items	Sources
	AW4: My bank has given me advice on how to utilize the banking chatbot.	
Behavioural Intention to use banking chatbots (BI)	BI1: I consent to using a chatbot to initiate transactions with my bank. BI2: I anticipate interacting with my bank on a regular basis using chatbots BI3: I intend to use chatbots for my future banking activities.	(Sugumar & Chandra, 2021; Venkatesh et al., 2003; Venkatesh et al., 2012)

4.2 Questionnaire design and data collection

To empirically test the model and hypotheses developed in the preceding section, the survey method was used based on a Bangladeshi sample. The survey utilized a questionnaire designed to collect data regarding the intention to use banking chatbots in Bangladesh. The questionnaire was structured into three distinct sections to gather comprehensive data. Part A contained demographic information, where respondents provided details on their age, gender, educational level, occupation, monthly income (in BDT), and geographical location (city). Part B aimed to capture insights regarding the respondents' use of banking chatbots. This section included questions about their capacity to use banking chatbots, methods of accessing chatbots, and the purpose and frequency of their usage. Part C contained items related to the constructs outlined in the research model, as illustrated in Figure 1. A five-point Likert scale was employed to measure these constructs, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), with a midpoint of 3 representing a Neutral stance.

Convenience sampling was followed in this study due to limited time and resources. Although this approach may limit generalizability due to potential bias, it is suitable for the exploratory study conducted under resource constraints (Golzar et al., 2022). Digitally literate segments of the Bangladeshi population who are more likely to be familiar with emerging technologies were considered highly relevant samples for this study. Therefore, current or former university students and bank employees were targeted for data collection. Generally, university students exhibit high engagement with new digital tools, while bank employees are frequently exposed to banking innovations through their professional roles. Thus, the selected population enhances the relevance and validity of the findings. Researchers leveraged their personal connections and professional networks to reach and engage these groups efficiently. The questionnaire was distributed online via Google Forms. Digital platforms like Facebook Messenger and WhatsApp groups were used to ensure broad and accessible participation. Data was gathered from June to July 2024.

A total of 330 responses (66%) of the 500 issued questionnaires were returned. After removing errors and incomplete responses, 324 responses were used for further analysis. Therefore, the final sample size of this paper is 324. Studies using Structural Equation Modeling (SEM) for analysis should aim for a sample size of 200 to be considered fair and 300 for good (Hair et al., 2014; Kline, 2015). Roscoe (1969) also reports that when conducting multivariate research, such as multiple regression analysis, the sample size should be at least 10 times the number of items in the study. Therefore, sample size 324 is adequate for this sample suggested by the scholars.

4.3 Data analysis method

Structural Equation Modeling (SEM) is widely recognized for its effectiveness in theory development and testing, and it has become a quasi-standard in research (Hair et al., 2012; Ringle et al., 2012). The proposed model is evaluated and validated using a statistical technique rooted in SEM known as the Partial Least Squares (PLS) method. The data were analyzed using SmartPLS. This is a well-known software for PLS-SEM (Sarstedt et al., 2022). Questionnaire data were initially entered into Microsoft Excel and subsequently imported into SmartPLS 4 software (Ringle et al., 2022) for statistical analysis.

This study followed the guidelines of Hair et al. (2021) to evaluate the measurement and structural models, ensuring reliable and robust PLS-SEM results. However, predictive evaluation procedures such as PLSpredict and model comparison techniques (e.g., Bayesian Information Criterion, Geweke-Meese criterion, and Akaike weights) were deliberately excluded in this study due to the presence of a formative construct (i.e., AW) and a single-item construct (i.e., BI), which limit the reliability and suitability of these tools. These procedures generally require reflective multi-item constructs and indicator-level detail to generate meaningful results (Shmueli et al., 2019). Besides, the goal of this study was to explore theoretical relationships and validate a context-specific extension of the UTAUT2 framework, rather than conduct predictive benchmarking, which supports the deliberate omission of these techniques.

5. Results

5.1 Demographic analysis

As stated earlier, 324 questionnaires were used for further analysis. Table 2 presents the demographic profile of respondents in terms of gender, age, educational attainment, occupation, monthly income (in BDT), and geographical location.

Table 2: Demographic analysis of respondents

Respondents' characteristics	Description	Frequency (n=324)	Percentage (%)
Gender	Male	178	54.9
	Female	146	45.1
Age	Below 21	6	1.9
	21–30	288	88.9
	31–40	24	7.4
	41–50	5	1.5
	Above 50	1	0.3
Educational level	Below Undergraduate	12	3.7

Respondents' characteristics	Description	Frequency (n=324)	Percentage (%)
	Undergraduate	147	45.4
	Graduate	61	18.8
	Post-graduate and above	104	32.1
Occupation	Employed (including business owner, freelancer)	103	31.8
	Student	201	62.0
	Other (unemployed, homemaker)	20	6.2
Monthly income (in BDT)	Below 20,000	213	65.7
	21,000–30,000	23	7.1
	31,000–40,000	29	9.0
	41,000–50,000	14	4.3
	Above 50,000	45	13.9
Geographical location	Dhaka	294	90.7
	Chattogram	9	2.8
	Khulna	4	1.2
	Rajshahi	4	1.2
	Rangpur	5	1.5
	Mymensingh	2	0.6
	Sylhet	2	0.6
	Barisal	4	1.2

The result revealed a gender distribution of 54.9% males and 45.1% females who participated in this study. A significant majority of participants, comprising 88.9%, were between the ages of 21 and 30 years. Regarding educational attainment, 45.4% of respondents held an undergraduate degree, while 32.1% had achieved postgraduate or higher education levels. The occupational profile showed that 62% of the respondents were students, whereas 31.8% were employed. Concerning monthly income, 65.7% of the respondents earned less than 20,000 BDT. Additionally, 90.7% of the respondents resided in Dhaka.

Table 3 summarizes the descriptives of banking chatbot usage among respondents. The table highlighted that a significant majority of respondents, 85.5%, used banking chatbots only as customers exclusively for personal banking needs, while 14.5% of participants used chatbots both as customers and employees for personal and work-related tasks. Among the various platforms (e.g., mobile banking app, bank's website, messaging apps, SMS/Text messaging, social media, and voice-activated assistants) for accessing these chatbots, 49.4% of users employed a combination of platforms, with the mobile banking app being the most frequently used at 35.5%. Additionally, 54.6% of participants interact with chatbots occasionally, highlighting a predominant usage pattern. Notably, 71.6% of respondents utilize chatbots for a range of purposes beyond a single function, demonstrating the multifunctional role of chatbots in banking.

Table 3: Descriptives of banking chatbot usage among respondents

Respondents' characteristics	Description	Frequency (n=324)	Percentage (%)
Capacity for using banking chatbots	Both as a customer and an employee (for personal and work-related tasks)	47	14.5
	Only as a customer (for personal banking needs)	277	85.5
Platforms used to access banking chatbots	Bank's website	19	5.9
	Messaging apps (e.g., WhatsApp, Telegram)	6	1.9
	Mobile banking app	115	35.5
	SMS/Text messaging	10	3.1
	Social media platforms (e.g., Facebook, Twitter)	11	3.4
	Voice-activated assistants (e.g., Google Assistant, Amazon Alexa)	1	0.3
	Different combinations of the above platforms	160	49.4
	I do not use banking chatbot.	2	0.6
Frequency of using banking chatbots	Multiple times a day	31	9.6
	Occasionally	177	54.6
	Once a day	16	4.9
	Once a week	22	6.8
	Several times a week	78	24.1
Purpose of using banking chatbots	Checking account balance	45	13.9
	Fast bill payments	1	0.3
	Fraud detection and alerts	2	0.6
	Immediate transaction confirmations	9	2.8
	Viewing transaction history	8	2.5
	Quick fund transfers between accounts	3	0.9
	Quick responses to queries	20	6.2
	Secure account management	2	0.6
	Different combinations of the above purposes	232	71.6
	Not using chatbots for any purpose	2	0.6

5.2 Measurement model

Internal reliability, convergent validity, and discriminant validity were assessed to validate the measurement model (Hair et al., 2013). Internal reliability was determined using Cronbach's alpha (α) and Composite Reliability (CR), with values above 0.70 indicating acceptable internal consistency (Hair et al., 2010). Convergent validity was assessed through average variance extracted (AVE) and item loadings, with an AVE of 0.50 or higher indicating adequate construct validity (Hair et al., 2013). Table 4 presents each construct's item loadings, AVE, CR, and Cronbach's alpha (α). The table indicates that Cronbach's alpha values ranged from 0.833 to 0.910, while composite reliability values ranged from 0.900 to 0.937, demonstrating robust internal reliability. Furthermore, item loadings ranging from 0.804 to 0.921 and AVE values ranging from 0.714 to 0.821 confirm the robust convergent validity within this study.

Table 4: The measurement model

Constructs	Items	Loading	Average Variance Extracted (AVE)	Composite Reliability (CR)	Cronbach's Alpha (α)
Awareness of service (AW)	AW1	0.838	0.714	0.909	0.867
	AW2	0.883			
	AW3	0.853			
	AW4	0.804			
Behavioral Intention to use banking chatbots (BI)	BI1	0.846	0.749	0.900	0.833
	BI2	0.870			
	BI3	0.880			
Effort Expectancy (EE)	EE1	0.919	0.821	0.932	0.891
	EE2	0.878			
	EE3	0.921			
Performance Expectancy (PE)	PE1	0.899	0.788	0.937	0.910
	PE2	0.906			
	PE3	0.903			
	PE4	0.842			
Perceived privacy risk (PPR)	PPR1	0.868	0.772	0.931	0.904
	PPR2	0.878			
	PPR3	0.905			
	PPR4	0.864			
Social Influence (SI)	SI1	0.896	0.794	0.921	0.871
	SI2	0.908			
	SI3	0.869			

Conversely, discriminant validity was evaluated using the Heterotrait-Monotrait Ratio (HTMT), which compares correlations across different constructs (heterotrait) with those within the same construct (monotrait) (Hair et al., 2017). This approach is widely recognized and recommended for its superior ability to evaluate construct distinctiveness in measurement models and to provide more consistent and reliable outcomes than traditional approaches

(Henseler et al., 2015). Table 5 displays that all HTMT values were below the recommended threshold of 0.90, confirming strong discriminant validity across all constructs in this study.

Table 5: Heterotrait-Monotrait (HTMT) Ratio

	AW	BI	EE	PE	PPR	SI
AW						
BI	0.606					
EE	0.442	0.674				
PE	0.471	0.733	0.761			
PPR	0.114	0.340	0.415	0.292		
SI	0.498	0.519	0.527	0.578	0.309	

5.3. Structural model

To determine the relationships between each construct in the proposed research model, a structural model was developed. First, common method bias and multicollinearity were assessed using Variance Inflation Factors (VIFs). As presented in Table 6, all VIF values were below the conservative threshold of 3 (Hair et al., 2019), indicating that the model is free from significant collinearity and common method bias.

Table 6: Variance Inflation Factors (VIF)

Path	VIF Values
PE -> BI	2.072
EE -> BI	2.079
SI -> BI	1.431
PPR -> BI	1.187
AW -> PE	1.000
AW -> EE	1.000
AW -> PPR	1.000

Second, the study employed path coefficient (β) and t-statistics to assess the link between independent and dependent variables. Table 7 displays the PLS results of the structural model.

Table 7: Hypothesis testing results

Hypothesis	Path	Path coefficients (β)	t-statistics	P values	Results
H1	PE -> BI	0.417	5.961	0.000	Accepted
H2	EE -> BI	0.216	3.040	0.002	Accepted
H3	SI -> BI	0.106	1.889	0.059	Rejected
H4	PPR -> BI	0.090	2.189	0.029	Accepted
H5	AW -> PE	0.426	6.484	0.000	Accepted
H6	AW -> EE	0.393	6.103	0.000	Accepted

Hypothesis	Path	Path coefficients (β)	t-statistics	P values	Results
H7	AW -> PPR	0.109	1.505	0.132	Rejected

The analysis revealed that the relationships between PE and BI (t =5.961, β = 0.417, $p < 0.05$), EE and BI (t = 3.040, β = 0.216, $p < 0.05$), PPR and BI (t = 2.189, β = 0.090, $p < 0.05$), AW and PE (t = 6.484, β = 0.426, $p < 0.05$), AW and EE (t = 6.103, β = 0.393, $p < 0.05$) were statistically significant. Consequently, hypotheses H1, H2, H4, H5, and H6 were accepted. In contrast, the relationships between SI and BI (t = 1.889, β = 0.106, $p > 0.05$) and AW and PPR (t = 1.505, β = 0.109, $p > 0.05$) were not statistically significant. Therefore, hypotheses H3 and H7 were rejected in this study.

Next, the R^2 value was calculated to evaluate the structural model's explanatory power. The R^2 for BI (0.469) indicated that the model explained 46.9% of the variance in behavioral intention to use banking chatbots, reflecting a moderate level of predictive power. In contrast, EE, PE, and SI demonstrated lower explanatory strength, while PPR contributed minimally, highlighting the differential impact of predictors across the model. The effect sizes of the direct relationships between exogenous and endogenous variables in this study were evaluated using the f^2 effect size. AW exerted a moderate impact on PE ($f^2 = 0.222$) and EE ($f^2 = 0.183$), while its impact on PPR was minimal ($f^2 = 0.012$). Among the predictors of BI, PE demonstrated the strongest effect ($f^2 = 0.158$), followed by EE ($f^2 = 0.042$), SI ($f^2 = 0.015$), and PPR ($f^2 = 0.013$), all indicating low effect sizes (Hair et al., 2019).

6. Discussion

This study used the UTAUT2 model extended with two external variables, such as PPR and AW, to determine the customers' behavioral intention to adopt the chatbot services for banking endeavors. The findings will inform future chatbot service development and enable banks to craft more targeted marketing strategies to support chatbot adoption in the banking sector.

This study reveals a significant positive relationship between PE and BI to adopt chatbots for banking activities, which implies that bank customers emphasize the performance and usefulness of chatbot technology. The result matches the study of Sugumar & Chandra (2021), which shows a similar impact of PE on BI, but contradicts the findings of De Andrés-Sánchez & Gené-Albesa (2023), where PE shows no meaningful impact. Interestingly, this result also contrasts with the findings of Hasan et al. (2023) that emphasize that Perceived Usefulness (conceptually equivalent to PE within the UTAUT2 framework used in this study) has no substantial effect on BI in the same national context. These contradictory findings within the context of Bangladesh suggest a notable shift in customer perceptions regarding the adoption of chatbots for banking services.

Unlike the findings of Hasan et al. (2023) that imply limited customers' awareness of chatbot benefits, this study indicates that customers now recognize the functional value of chatbots in performing banking activities. The perceptual shift may result from increased exposure to AI-based banking tools, improved system capabilities, and growing digital literacy. Therefore, by capturing this evolution, this study demonstrates that PE remains a key factor in adopting chatbots in emerging economies like Bangladesh, which are experiencing rapid digital transformation.

This study also finds a positive and significant relationship between EE and BI to adopt chatbot services, consistent with previous research (Alt et al., 2021; De Andrés-Sánchez & Gené-Albesa, 2023). When chatbot services are perceived as easy to use, banking customers are more likely to engage with them. This finding is particularly relevant in the Bangladeshi context, where limited technological literacy heightens the demand for user-friendly technologies. Notably, Hasan et al. (2023) also report a similar association within Bangladesh, further reinforcing the critical role of EE in shaping user adoption behavior.

Moreover, this study doesn't find any positive relationship between SI and BI in adopting banking chatbot services in Bangladesh. While Marak et al. (2025) observe that peer usage and social recommendations positively influence banking chatbot adoption in India, this study's findings align with Sugumar & Chandra (2021), who report no such impact across India, Singapore, and the USA. The divergence within South Asian contexts may stem from differences in digital maturity, cultural orientation, and the pace of AI integration. As stated earlier, in Bangladesh, chatbot services are still relatively new, and users may not yet see widespread peer adoption or social endorsement as credible cues to use chatbots. This study indicates that Bangladeshi users rely more on personal assessments of usefulness and ease of use than on social influence when deciding whether to adopt chatbot services. Therefore, this study highlights the need to interpret chatbot acceptance through localized behavioral and infrastructural lenses.

In the same way, the findings of this study indicate that PPR negatively impacts BI to adopt banking chatbots. Although previous research on the adoption of m-banking and i-banking presents similar results (Arif et al., 2016; Giovanis et al., 2012), the findings contrast with the results of Alt et al. (2021), which report that PPR has no effect on banking chatbot usage intention in Romanian banks. The divergence in customers' chatbot adoption intention in banking services may reflect differences in digital trust, regulatory environments, and consumer awareness between the two countries. In Bangladesh, customers are highly concerned about data protection and technological transparency. As a result, they are less interested in using any technology that compromises their personal data. This study emphasizes that privacy assurance is important in shaping customers' chatbot adoption behavior. Banks must proactively address privacy concerns to foster trust and encourage chatbot usage.

Finally, this study identifies that AW positively influences both PE and EE, but has no significant effect on PPR, consistent with the findings of Alt et al. (2021). These findings imply that when banks can create more awareness regarding chatbot services, customers are more likely to perceive them as useful and easy to use. However, in the Bangladeshi context, increased awareness alone does not alleviate privacy concerns. Therefore, the study suggests that trust-building efforts must extend beyond informational outreach.

7. Implications

7.1 Practical Implication

This study can be used as an informative and useful guideline for financial institutions, technology developers, and policymakers seeking to foster sustained chatbot adoption in Bangladesh's banking sector. These stakeholders must collaborate to unlock the full potential of chatbot technology through coordinated and targeted efforts. Banks should lead this initiative by raising customers' awareness through in-app tutorials, SMS alerts, and public webinars to promote informed chatbot usage. They can also implement performance dashboards and periodic satisfaction surveys to monitor customer engagement and refine chatbot services based on user feedback. Technology developers must design mobile-friendly interfaces with voice and multilingual (i.e., Bengali and English) support and embed consent-based data handling mechanisms to address privacy concerns and improve accessibility. They can also incorporate real-time help prompts and design chatbots that work in low-bandwidth conditions to widen chatbot adoption across diverse user segments. At the policy level, strategic planners must enact and enforce transparent data protection regulations while establishing national AI standards for banking applications. They can further invest in digital literacy programs to ensure widespread acceptance of chatbot technologies in Bangladesh. The collective initiatives can encourage chatbot usage in banking while protecting customer privacy and promoting industry expansion.

7.2 Theoretical Implication

This study provides a substantial theoretical addition to the body of research. Models of technology acceptance are widely used to investigate how users embrace new technologies. The UTAUT2 model was used in this study to examine behavioral intentions to use chatbot services in a developing country. Most previous studies either employed the basic TAM or UTAUT paradigm with PE and EE components in developed nations or paid little attention to the uptake of chatbot services. This study presents the first experimental evaluation of the UTAUT2 model in the context of banking chatbot adoption in Bangladesh, extending the framework by incorporating additional variables such as PPR and AW. With further factors alongside core UTAUT2 constructs, the findings offer strong empirical support for the model's applicability in banking-related chatbot services and reinforce its relevance in emerging digital environments.

8. Limitations and Future Research Directions

This study has some limitations that open the window for further research. This paper focused on all the ages of the people who adopt chatbots in their banking services; future studies could be more specific regarding age differences or occupation differences. Likewise, the UTAUT model could be incorporated by adding other external variables, such as self-efficacy, technological anxiety, or perceived value. In the analysis section, future research may also incorporate out-of-sample prediction and model comparison in assessing the structural model for broader generalizability. Longitudinal data could be used in future research to better reflect real technology usage and reveal the causal relationship between factors over time.

9. Conclusion

The study employs the UTAUT2 framework with external variables, including PPR and AW in a developing nation, to discover the elements that influence customers' intentions to embrace chatbots in banking operations. The findings of the study indicate that the intention to use chatbot services is positively affected by performance expectancy, effort expectancy, and perceived privacy risk. Aside from the apparent privacy danger (i.e., perceived privacy risk), awareness of service positively influences performance expectancy and effort expectancy. This study advances the existing literature by providing empirical insights into the design and development of chatbot software to enhance its adoption and acceptance across financial industries. The findings also offer critical insights for technology developers, strategic planners, and policymakers in formulating context-sensitive strategies and regulatory frameworks to support the effective deployment and accelerated uptake of chatbot technologies among end users in emerging economies like Bangladesh.

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Conflicts of Interest

The authors declare no conflict of interest.

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