Exploring the Factors Influencing Cambodian Consumers' Intention to Use AI Banking Chatbot

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Abstract

The adoption of artificial intelligence (AI) is reshaping the global banking industry, yet there is limited understanding of consumer acceptance of AI chatbots in developing countries such as Cambodia. This study explores the factors influencing Cambodian consumers' behavioral intention to use AI chatbots in banking sector. With the Technology Acceptance Model (TAM), extended with constructs from the Unified Theory of Acceptance and Use of Technology (UTAUT), Innovation Diffusion Theory (IDT), and additional variables including trust in AI, perceived risk, privacy concern, anthropomorphism, and perceived interactivity, a conceptual model was developed and tested using survey data from 228 respondents. Structural equation modeling (SEM) and mediation analysis were employed to validate the model. The findings reveal that social influence is significant influence behaverioal intention to use AI banking Chatbot as well as perceived usefulness and compatibility are the most significant drivers of AI banking Chatbot adoption, with compatibility having a mediation effect through perceived usefulness. In contrast, trust in AI, perceived risk, privacy concern, and anthropomorphism did not significantly shape behavioral intention to use. Perceived interactivity was found to enhance trust in AI, though trust in AI itself did not enhance the behavioral intention to use. These results highlight that Cambodian consumers prioritize functional benefits and contextual fit over social or psychological factors when adopting an AI banking Chatbot. The study contributes to the literature on technology adoption in developing countries and provides actionable recommendations for banks and policymakers in Cambodia to design and implement AI chatbot solutions that align with consumer needs.

Keywords: AI banking Chatbot, TAM, artificial intelligence, compatibility, behavioral intention to use, Cambodia, perceived usefulness, banking sector

1. Introduction

The adoption of artificial intelligence in banking is rapidly growing, with global spending predicted to reach $84.99 billion by 2030 (Statista & Juniper Research, 2024). In Cambodia, although artificial intelligence is still in early stages, it is no longer a futuristic term as it rapidly grows, driven by various sectors and by the offering of AI-related courses from many educational institutions (Fidero et al., 2023). In 2023, banks worldwide made about $1,439 billion in profit by using AI. Normal growth would increase this to $1,822 billion by 2028. The adoption of AI in banking is projected to add $170 billion to global banking profits by 2028, potentially bringing total sector profits to $1,992 billion. This significant impact underscores the growing importance of AI and chatbot technologies in revolutionizing the banking industry and improving operational efficiencies (Statista, 2025). Many people have been interacting with AI daily that including chatbots (Maduku et al., 2025). Chatbots are recognized as one of the most commonly employed forms of artificial intelligence (Eren, 2021). An AI Chatbot is a conversational agent powered by artificial intelligence technologies such as natural language processing, natural language understanding, and machine learning (Rawat et al., 2024). It is becoming increasingly difficult to avoid AI Chatbots, which are used to collect, organize, process, and deliver customized services to banks (Ngai et al., 2021). By 2025, 73% of banks across the world will use AI-powered chatbots, and the market is expected to be worth $49.9 billion by 2030 (Vedant, 2025). In the banking sector, chatbots act as virtual assistants, offering customers instant support for queries such as account balances, loan applications, transaction history, and product recommendations (Chokkalingam et al., 2024). A few bank in Cambodia begins to integrate artificial intelligence to improve service efficiency and accuracy. For instance, Wing Bank has also invested in AI for real-time cybersecurity monitoring, customer profiling, loan approval, and developing a large language model Khmer (Rishi, 2025). Advanced Bank of Asia Ltd. (ABA Bank) is the first financial institution in Cambodia to implement an AI-powered assistant called “Navi,” which supports customers in Khmer, English, and Chinese, making banking services accessible to diverse users while operating 24/7 through the ABA Mobile application (ABA, 2025). These examples show that Cambodia’s banking sector is progressively leveraging AI to enhance customer service and financial inclusion.

Although AI adoption in Cambodia's banking sector is increasing, there remains a lack of research investigating consumer acceptance of AI Chatbots and examining the factors influencing the usage intention of AI Chatbots in Cambodia. According to Ayantola (2023), the use of generative AI for economic and social effects in developing countries is not receiving enough attention in the present global discussion. Although the usage of chatbots in financial services has been widely studied in the past, little is known about how customers in developing countries interact with banking chatbots, despite the increasing understanding of how FinTech affects consumer behavior (Mogaji et al., 2021). In Cambodia, there are a few existing studies that investigate AI, but they primarily focus on other areas. For instance, Pum & Sok (2024) studied the concerns and benefits associated with using artificial intelligence in the education system in Cambodia, while Heng et al. (2022) studied how artificial intelligence ecosystems are constructed and function in Global South countries, with a specific focus on Senegal and Cambodia. There has been no academic or empirical study conducted to explain users' acceptance of AI banking Chatbot in Cambodia. This creates a knowledge gap in understanding how Cambodian consumers adopt AI banking Chatbot. Furthermore, the Royal Government has set policies to promote the adoption of new technologies such as artificial intelligence, machine learning, big data, cloud computing, blockchain, smart contracts, natural language processing, virtual reality, and data analysis to drive innovation in the financial sector. Among these policies, one key focus is the promotion of innovative digital banking products and services to foster the development and innovation of Cambodian FinTech activities (Aun, 2023). However, without research on consumer readiness, banks risk investing in technologies that may not match customer expectations. These studies would allow researchers to explore the factors influencing the intention to use AI banking. Specifically, it aims to identify how Cambodian consumers perceive and experience AI banking Chatbot, determine the key drivers such as perceived usefulness, perceived ease of use, compatibility, trust in AI, anthropomorphism, social influence and perceived interactivity, assess barriers such as perceived risk and privacy concern, and provide recommendations for banks in Cambodia and policymakers on enhancing chatbot services tailored to the unique characteristics of Cambodian consumers. We thus aim to answer the following research question: How do Cambodians view and experience AI banking Chatbot? What are the key drivers and acceptance of AI banking Chatbot in Cambodia?

To address this research gap, we constructed a conceptual model based on the Technology Acceptance Model (Davis, 1989) as the main framework. The variables include trust in AI, perceived risk, perceived usefulness, perceived ease of use, compatibility, social influences, perceived interactivity, anthropomorphism, privacy concern, and behavioral intention to use. And we conduct a questionnaire with Qualtrics and then distribute it to social media, mainly Facebook. The analyses suggest that Cambodian consumers prioritize perceived usefulness, compatibility, social influence and perceived interactivity over trust in AI, privacy concern, or anthropomorphism when adopting an AI banking Chatbot. This study demonstrates that perceived usefulness and compatibility are central mediating mechanisms in AI banking Chatbot intention to use in Cambodia.

This research is structured as follows: first, we outline a literature review and explain our concepts. Then we formulate our hypotheses, which are followed by the research methodology, including data collection and analysis procedures. Next, we present the results and the findings in relation to theory and practice, and finally, the last section provides conclusions, managerial implications, limitations, and directions for future research.

2. Literature Review

2.1 Artificial Intelligence and Chatbots

Artificial intelligence (AI) refers to the simulation of human cognitive functions by machines, which allows them to perform tasks like speech recognition, visual interpretation, and decision-making (J. Kim et al., 2022). Artificial intelligence has facilitated organizations in providing customized experiences through the anticipation of consumer preferences and the analysis of consumer data to offer more relevant product and service recommendations (Spais & Jain, 2025). AI assistants are reshaping the business environment by innovating customer service, sales, and marketing (X. Zhang et al., 2025). AI allows for the automation of many design tasks, which can lead to faster and more efficient processes. For instance, companies like Netflix and Airbnb use AI to personalize user experiences in real-time, creating solutions tailored to individual preferences (Verganti et al., 2020). Many of the systems people interact with daily, such as digital personal assistants like Siri, Google Assistant, Amazon Alexa, and Samsung's Bixby, and chatbots, are powered by AI (Maduku et al., 2025). A chatbot is defined as a program of a computer that engages in dialogue utilizing natural language, subsequently providing replies that are informed by organizationally established business protocols and data configuration (Balakrishnan et al., 2022).

Chatbot has two types, which are “text-based chatbots” that rely on text input and provide responses by analyzing keywords and patterns from the user’s message, and “speech-based Chatbots” which communicate using spoken language and use voice recognition technology to understand and respond (Rese et al., 2020).

Artificial intelligence (AI) has been employed to create conversational AI chatbots, which possess the capability to comprehend and react to input articulated in natural language. It implements methodologies including natural language processing (NLP), natural language understanding (NLU), and natural language generation (NLG) to interpret and address user interactions (Rawat et al., 2024). Chatbots are enhanced with Generative AI technology, which means that instead of giving scripted or preset answers, GenAI allows chatbots to come up with unique, context-aware responses that sound more natural and human-like (Arce-Urriza et al., 2025). AI Chatbot acts as a frontline service agent in settings such as retail and consumer services and helps customers to search for products, place orders, or provide service (Chong et al., 2021). AI Chatbot makes customer service faster and offers 24/7 support to respond to customer queries and support needs to ensure that customers receive timely assistance regardless of time or location. It also reduces the need for extensive human support teams and continuous training, leading to lower operational costs. This cost efficiency is essential for businesses, especially those with budget constraints, while maintaining quality service (Kaushal & Yadav, 2023).

2.2 AI Chatbot in Banking and Finance Sectors

According to Juniper Research, AI Chatbots are adopted in various sectors, including Banking & Finance, E-Commerce & Retail, Healthcare Industry, Media & Entertainment, and Travel & Hospitality (Juniper Research, 2023). The financial industry has steadily integrated the digital era, despite its traditional reliance on human resources. As new technologies emerge, financial offerings and services are now encompassed within the realm of Financial Technology (Eren, 2021). The principle of FinTech transcends basic e-banking and consumer digitalization, directing attention to the design and efficient utilization of leading-edge technological mechanisms crafted to fulfill users' financial requirements and expectations. In this context, AI presents a distinct opportunity to propel the evolution of the finance sector by delivering enhanced value to users while boosting the revenues of firms (Belanche et al., 2019). Traditional banking processes have been revolutionized by AI and have become more customer-centric and efficient. These AIs can manage a variety of customer interactions from basic questions to complex problem-solving and let human agents concentrate on difficult jobs (Othayoth & Khanna, 2025). In the banking sector, chatbots assist users by giving accurate responses for banking inquiries such as account balance, transaction history, fund transfer, loan application, and other common banking tasks, all through a user-friendly interface. It helps reduce the workload on human customer service representatives, allowing banks to maintain service standards even during peak time (Chokkalingam et al., 2024). For example, the Development Bank of Singapore (DBS) created a "digibot" to assist customers in conveniently checking products and services. The chatbot of the Commonwealth Bank of Australia (CBA), designed to assist customers with banking activities like making payments and checking account balances, also utilizes the eVisa Developer Platform to improve the fraud detection system implemented in the chatbots (Bouhia et al., 2022). In Cambodia, there are a few banks that already implement Chatbot applications (Heng et al., 2022).

2.3 Conceptual Framework and Hypotheses Development

The Technology Acceptance Model developed by Davis (1989) is a framework used to understand and predict how users accept and use a technology. Several scholars used TAM to explain a user's acceptance of new technology (Xavier et al., 2024). In TAM, there are two main constructs which are perceived usefulness and perceived ease of use. Perceived usefulness refers to the degree to which a person believes that using a technology will improve their job performance or make tasks easier, and perceived ease of use is the degree to which a person believes that using the technology will be effortless or easy to use (Davis, 1989). Both constructs influence the behavioral intention to use new technology. TAM has been wisely used in various contexts, including AI-powered voice assistants (Acikgoz et al., 2023), mobile apps (Vahdat et al., 2021), FinTech (Singh et al., 2020), Virtual reality devices (Lee et al., 2019), Augmented reality apps (Rese et al., 2017), and IoT smart home service (Y. Kim et al., 2017). In this study, perceived usefulness and perceived ease of use are central to understanding how Cambodians perceive the AI banking Chatbot. While TAM provides a strong baseline, it does not capture the broader social and contextual influences of technology adoption, especially the AI banking Chatbot in Cambodia. To address this matter, the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) is incorporated. UTAUT has also been used as a theoretical lens to study the user intention and behaviour towards various technologies (Williams et al., 2015), especially consumer interaction with banking chatbots (Mogaji et al., 2021). In this research use one construct of UTAUT, which is social influence. Social influence reflects the extent to which individuals perceive that important others believe they should use a particular technology (Venkatesh et al., 2003). We have also included the constructs from Innovation Diffusion Theory (IDT), which includes compatibility, to further enrich the framework (Rogers, 2003). Compatibility is counted and used to reflect how well the technology fits with users' values, needs, and experiences (Rogers, 2003). In the case of an AI banking Chatbot in Cambodia, we assume that it is crucial because users will adopt these systems only if they align with their existing practices, lifestyles, and financial service preferences. Additionally, trust in AI is included as a complementary factor as it helps users cope with the uncertainties and complexities associated with AI's decision-making processes, especially given the autonomous nature of AI systems (Choung et al., 2023). Moreover, perceived interactivity and anthropomorphism are also included to examine the attribution of human-like characteristics to AI systems, which enhances users' perceptions of engagement and responsiveness, making interactions feel more natural and acceptable (Epley et al., 2007; Kang et al., 2021). Building upon the fundamentals of TAM, UTAT, and IDT, as well as complementary constructs such as trust in AI, perceived risk, perceived interactivity, and anthropomorphism. These constructs aim to provide a holistic explanation of AI banking Chatbot intention to use in Cambodia by capturing both technology perceptions and psychological barriers, as shown in **Figure 1**.

2.3.1 Trust in AI and behavioural intention to use

Trust refers to the willingness to depend on another party in an exchange relationship, particularly, the readiness to believe that the trusted party will meet their responsibilities, be honest, and act in the best interest of the trustor (Mozafari et al., 2022). In the context of artificial intelligence, trust can be understood as a user's willingness to depend on an AI system, specifically, the belief that the AI will perform its tasks reliably, provide accurate and truthful information, and operate in alignment with the user's best interests. Trust plays a crucial role as a predictor in determining whether individuals choose to rely on AI advice (Klingbeil et al., 2024), while a significant barrier to the adoption of technological tools is the absence of trust (Gefen et al., 2003). We assume that in the context of AI banking Chatbot, Cambodians' willingness to adopt and continuously use these services is strongly influenced by trust in AI Chatbot. Kelly et al. (2023) studied existing research on user acceptance of AI technology by focusing on behavioral intention, willingness, and actual use, identifying key predictors, and evaluating the theoretical models (mainly TAM) applied across industries. This research found that trust significantly and positively predicted behavioral intention, willingness, and use behaviour of AI across multiple industries (Kelly et al., 2023). Similarly, another study on chatbots has found that trust positively impacts behavioral intention to use (Silva et al., 2023). In addition, Liu and Tao (2022) studied how trust and AI-specific characteristics affect people's intention to use AI-based smart healthcare services. The results show that trust is the central factor, mediating the effects of AI-specific characteristics on acceptance (Liu & Tao, 2022). Thus, in the context of an AI banking Chatbot, we assume, as in previous studies (Liu & Tao, 2022; Silva et al., 2023), that trust in AI has a significant positive impact on behavioral intention to use an AI banking Chatbot. Therefore, we formulate the following hypothesis:

- **H1**: Trust in AI positively impacts behavioral intention to use.

2.3.2 Perceived risk and behavioral intention to use

Perceived risk refers to the consumer's feeling of uncertainty or concern that something might go wrong when using or adopting an e-service (Featherman & Pavlou, 2003). In the context of an AI banking Chatbot, perceived risk refers to the feeling of concern about potential negative outcomes that users have when using the AI banking Chatbot. For instance, Featherman et al. (2010) noted that technologies used in financial and health services carry higher privacy risks for users, since the information they store is highly personal and sensitive. Additionally, prior research examines the relationship between perceived risk and behavioural intention to use in chatbots and finds that perceived risk negatively affects behavioural intention to use (Natarajan et al., 2017). Regarding the study of e-banking contexts, research has confirmed that perceived risk negatively affects behavioral intention use (Abikari, 2024). For instance, Chauhan et al. (2022) found a significant negative impact of perceived risk on user intention to adopt emerging e-banking services. Thus, from the perspective of an AI banking Chatbot, we assume that perceived risk negatively impacts behavioral intention to use. Therefore, the following hypothesis is proposed:

- **H2:** Perceived risk negatively impacts behavioral intention to use.

2.3.3 Perceived ease of use and behavioural intention to use

Perceived ease of use refers to the degree to which a person believes that using a particular system would be free of effort (Davis, 1989). In the context of an AI banking Chatbot, perceived ease of use reflects Cambodians' perception of how simple and easy the AI banking Chatbot is when performing tasks, such as understanding the reason behind a query, whether it's checking an account balance, making a transfer, or seeking information about loan options (Chokkalingam et al., 2024). According to Davis (1989), users are unlikely to adopt a technology if it fails to fulfill its intended purpose, regardless of how easy it is to use. Thus, from the perspective of an AI banking Chatbot, Cambodians will not use an AI banking Chatbot if it fails to answer and fulfill Cambodian users. Numerous studies have empirically examined the concept of perceived ease of use and confirmed its significant and positive impact on the adoption of chatbots (Gopinath & Kasilingam, 2023), and GPT-powered virtual medical consultation systems (D. Zhang & Zhao, 2024). Thus, within the scope of an AI banking Chatbot, we assume, based on the research by Gopinath and Kasilingam (2023) and D. Zhang and Zhao (2024), that perceived ease of use affects positively and plays a more prominent and meaningful role in influencing intention to use an AI banking Chatbot. So, the research hypotheses in this study are as follows:

- **H3**: Perceived ease of use positively impacts behavioral intention to use.

2.3.4 Perceived usefulness and behavioural intention to use

Perceived usefulness is defined as the degree to which an individual believes that using a technology will help improve their performance (Davis, 1989). In the context of an AI banking Chatbot, perceived usefulness refers to the degree to which a user believes that using an AI banking Chatbot will enhance their banking efficiency performance. For instance, a chatbot can assist users and provide 24/7 service (Alt et al., 2021). Perceived usefulness is defined as a significant antecedent of users' intention to adopt the technology in areas such as mobile banking (Foroughi et al., 2019), and the adoption of robo-advisors in the FinTech sector (Belanche et al., 2019). In chatbot research, perceived usefulness plays a crucial role and has been shown to positively influence users' intention to use (Rese et al., 2020). So, in the framework of an AI banking Chatbot, we assume, as in a previous study on the factors influencing user adoption of AI-based chatbots in service encounters (Gopinath & Kasilingam, 2023), that perceived usefulness has a positive influence on behavioral intention to use an AI banking Chatbot. Accordingly, this study hypothesizes that:

- **H4:** Perceived usefulness positively impacts behavioral intention to use.

2.3.5 Compatibility between perceived usefulness and perceived ease of use

Compatibility is one of the constructs of Innovation Diffusion Theory by Rogers (2023), and refers to the extent to which an innovation is perceived as consistent with an individual's existing values, prior experiences, lifestyle, and current needs. A higher degree of perceived compatibility is associated with a greater likelihood of adoption (Rogers, 2003). In the context AI banking Chatbot, compatibility refers to how well the use of an AI banking Chatbot is compatible with users' experiences, lifestyle, and current needs. Individuals who perceive a new technology as compatible with their values and experiences are better equipped to assess its perceived usefulness and are more likely to view it as easier to use (Giovanis et al., 2012). Koenig-Lewis et al. (2010) studied to barriers to adopting mobile banking services and found that compatibility has a positive effect on perceived usefulness, and it positively influences perceived ease of use. Within the framework of an AI banking chatbot, we assume, as in a prior study on the adoption of mobile banking services (Koenig-Lewis et al., 2010), that compatibility positively influences perceived ease of use and perceived usefulness. Thus, we hypothesize that:

- **H5a:** Compatibility positively impacts perceived ease of use.
- **H5b:** Compatibility positively impacts perceived usefulness.

2.3.6 Social influence with perceived usefulness and behavioural intention to use

Social influence refers to how users perceive that important others think they should use the technology (Venkatesh et al., 2003). In the context of the adoption of AI banking Chatbot in Cambodia, this means that Cambodians may perceive the AI banking Chatbot as useful and decide to use it if they believe that those influential people around them consider the use of the AI banking Chatbot to be important and beneficial. Social influence plays a significant role in shaping users' behavioral intention, including chatbots (Gopinath & Kasilingam, 2023). In addition, there is a positive correlation between social influence and both perceived usefulness and behavioral intention to use (Venkatesh et al., 2003). Many empirical studies validate that social influence has a direct effect on both perceived usefulness and behavioral intention to use across domains, including the automated vehicle (T. Zhang et al., 2020) and mobile devices for learning (Park et al., 2012), and these empirical studies found that social influence positively impacts perceived usefulness and behavioral intention to use. Considering the AI banking Chatbot, we assume that social influence positively influences perceived usefulness and behavioral intention to use. Based on this, the following hypothesis is proposed:

- **H6a**: Social influence positively impacts perceived usefulness.
- **H6b**: Social influence positively impacts behavioral intention to use.

2.3.7 Perceived interactivity and trust in AI

Perceived interactivity refers to the ability of users to engage in active, two-way communication within a digital platform (Kang et al., 2021). In the context of an AI banking Chatbot, perceived interactivity refers to the conversation and interaction between the user and the AI banking Chatbot. The interactivity of chatbots serves as an indicator of their proficiency in engaging with clients, their capability to address the inquiries presented by users, and the promptness with which these automated systems respond to such inquiries (Ding & Najaf, 2024). Based on existing research, interactivity plays a crucial role in shaping consumers' trust in AI chatbots (Sun et al., 2024). Prior study found that users perceive a higher degree of interactivity, their level of trust tends to increase accordingly, and this study supports the utility of interactivity as it positively impacts trust for the user (Cyr et al., 2009). In the case of AI banking Chatbot, we assume that perceived interactivity significantly positive influence on trust in AI. Thus, the following hypotheses are proposed:

- **H7:** Perceived interactivity positively impacts trust in AI.

2.3.8 Privacy concern and trust in AI

Privacy concern refer to the worries or apprehensions that individuals have about the collection, use, storage, and sharing of their personal data by organisations or technologies (Xu et al., 2023). Recently, privacy has become a significant topic within AI literature, particularly in the realm of AI (Bouhia et al., 2022; McLean & Osei-Frimpong, 2019). In the context of interacting with the

AI banking Chatbot, privacy concern becomes particularly pronounced. Since chatbots often request sensitive information to provide services and this leads users to worry about the possibility of such information being mishandled or falling into the wrong hands (Bouhia et al., 2022). Privacy concern is a significant barrier to user self-disclosure when interacting with AI banking Chatbot, and users interacting with their preferred banking brand's chatbot disclosed less personal information and had lower brand trust compared to those interacting with a fictitious brand (Lappeman et al., 2023). We propose that privacy concern reduces the level of user trust due to fear related to personal data that consumers experience with AI. Therefore, we assume that privacy concern has a negative impact on trust in AI. We hypothesize:

- **H8**: Privacy concern negatively impact trust in AI

2.3.9 Anthropomorphism between Trust in AI

Anthropomorphism describes the inclination to attribute humanlike characteristics such as emotions, intentions, or actions to nonhuman entities (Epley et al., 2007). Anthropomorphism is one factor of perceived humanness, and the other two factors are conversational human voice and social presence (Lu et al., 2022). According to Araujo (2018), an anthropomorphic agent was programmed to engage participants through informal language, was given a human name, and participants were instructed to begin and end the interaction using conversational cues typically found in human-to-human communication, such as greetings and farewells. Previous research has applied the concept of anthropomorphism across various contexts, particularly in relation to AI technologies (Malhotra & Ramalingam, 2025), Chatbot service-based (Balakrishnan et al., 2022), and personal intelligent (Moussawi et al., 2021). In addition, Klein & Martinez (2023) indicate that anthropomorphic design in chatbots positively influences trust and suggest that chatbots should be designed to inspire trust, among other qualities, to attract customers through pleasant experiences. De Visser et al. (2016) indicate that anthropomorphized avatars can strengthen trust by helping users feel more connected and understood during interactions. In the context of AI banking Chatbot, we assume that anthropomorphized avatars of chatbot strengthen trust. Thus, we propose the following hypothesis as below:

- **H9:** Anthropomorphism positively impacts trust in AI

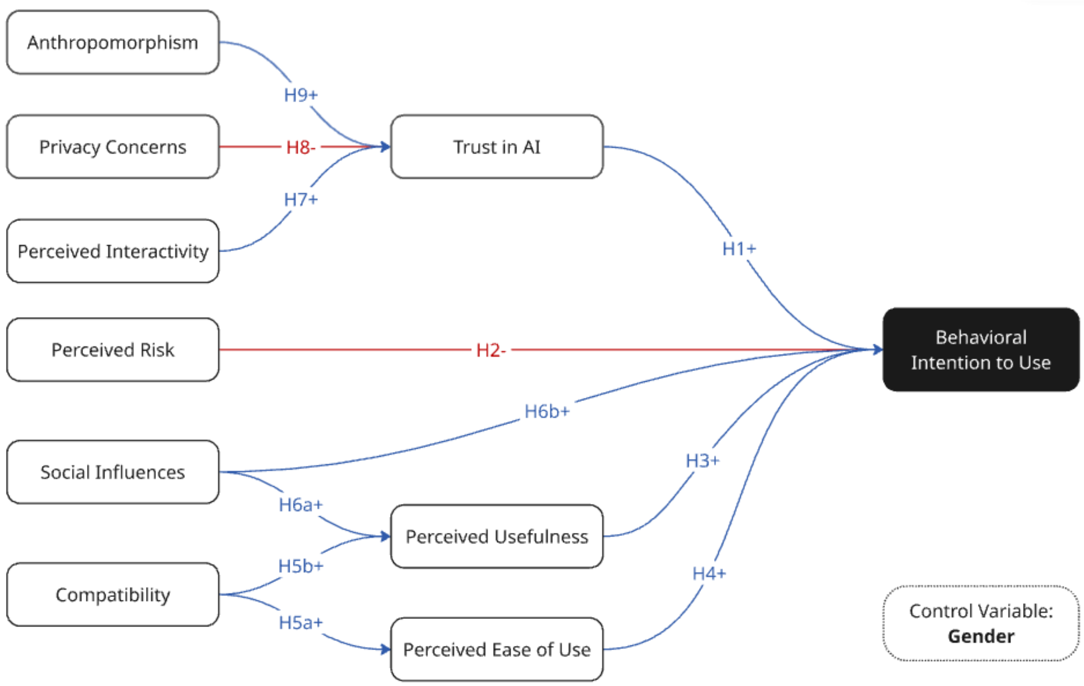


Figure1. Proposed Conceptual Model

3. Methodology

3.1 Sample characteristics

We surveyed by using Qualtrics and collected a total of 362 responses in Cambodia. To ensure data quality, we removed incomplete responses and filtered those with completion times of less than 200 seconds, resulting in a final dataset of **228 responses** for our detailed analysis. The average age of respondents was approximately 27.14 years. In terms of gender, 47.81% identified as male, 49.56% as female, and 2.63% preferred not to say. Regarding employment status, the sample consisted of individuals who were employed full-time (67.98 %), employed part-time (5.26%), unemployed looking for work (3.51 %), unemployed not looking for work (1.32 %), retired (0.88 %), and students (21.05 %). Concerning educational background, high school (3.51%), vocational training (0.44 %), university (60.09%), master's degree (33.33%), and PhD (2.63%). Among the 228 respondents, 74.12% had heard of AI Chatbots in Banking, and 25.88% had not. Furthermore, 44.74% reported having used an AI Chatbot, whereas 55.26% had not used them for banking or financial services in Cambodia.

We manipulate anthropomorphism by developing a scenario-based conversation between a customer and an AI banking Chatbot. Manipulation of anthropomorphism can be accomplished by giving a chatbot a name, gender, and avatar (De Visser et al., 2016; Waytz et al., 2014). For instance, prior research manipulated chatbot anthropomorphism between-subjects design in the context of online wine shopping (Konya-Baumbach et al., 2023). To examine the impact of anthropomorphism in this study, we randomly assign participants to two conditions which are high anthropomorphism and low anthropomorphism. In high anthropomorphism, participants interacted with a chatbot named *Sokha*, designed to resemble a human agent. Sokha used a human name, a friendly tone, emotional expressions, and relational language. The AI banking Chatbot also uses personalized greetings, small talk, and emotions to simulate a more lifelike interaction. For low anthropomorphism, participants interacted with a chatbot named *Chatbot N01*, which communicated in a formal, robotic tone. Its responses were task-oriented, lacking emotional expressions or personalization. The AI banking Chatbot avoided relational phrases and did not display social presence. We present participants with pictures of the conversation between an AI banking chatbot and a customer about loan inquiries and eligibility assessments **(Appendix 1)**. Anthropomorphism was measured by asking participants to rate three items adapted from Sun et al. (2024): I think the AI banking chatbot is “machine-like”, “unnatural”, and “artificial”.

3.2 Measurement Instruments

In this study, we analyzed the responses using RStudio. All measurement scales were based on and adapted from previous studies. The full-scale items can be seen in **Table 2**. Responses were collected based on a seven-point Likert scale (1 = Strongly disagree, 7 = Strongly agree). To measure privacy concern (PC), we adapted the scale from Bouhia et al. (2022). Perceived ease of use (PEU) and perceived usefulness (PU) are measured with the scale proposed by Ashfaq et al. (2020). Compatibility (COM) is measured using the scale proposed by Meuter et al. (2005), perceived risk (PR) is base on the scale of Silva et al. (2023), Trust in AI (TR) is measured using the scale proposed by Cheng et al. (2022), perceived interactivity (PI) is measured using the scale proposed by Cho et al. (2019), Social influence (SI) is measured using the scale proposed by Balakrishnan et al. (2022) and behavioral intention to use (BIU) is base on the scale of Venkatesh et al. (2012). Anthropomorphism is a manipulated variable that we measure by using a seven-point Likert scale (1 = Strongly disagree, 7 = Strongly agree). Anthropomorphism was measured by asking participants to rate the following three statements from Sun et al. (2024): I think the AI banking Chatbot is “machine-like”, “unnatural”, and “artificial”.

3.3 Assessment of the measurement model

In our analysis, we conducted exploratory and confirmatory factor analyses by using RStudio to test the proposed conceptual model in **Figure 1**. It reveals that all scales show satisfactory psychometric properties. During the confirmatory factor analysis process, items with weak standardized loadings (< 0.70) were removed to improve the measurement model’s reliability and validity. Specifically, we removed PC4, PEU1, PEU2, and TR1 based on their insufficient factor loadings. After this refinement, all remaining scales demonstrated good reliability (Cronbach’s Alpha > 0.7), (convergent validity > 0.5), and discriminant validity (r^2 < convergent validity; **see Tables 2 and 3**). The final measurement model achieved good fit according to the usual fit indices: RMSEA < 0.08, CFI > 0.90, and TLI > 0.90, the convergent validity (all convergent validity > 0.50) **(Table 1).**

Table 1. Fit Indices

χ^2	df	RMSEA	CFI	TLI
518.856	288.000	0.059	0.954	0.944

Table 2. Measurement scales, Reliability, and convergent validity

Construct	α	Conv. val.	Loadings	Sources
Privacy concern	**0.84**	**0.62**		(Bouhia et al., 2022)
PC1: When the AI banking Chatbot asks me for personal information, I sometimes think twice before providing it.			0.740	
PC2: It usually bothers me when the AI banking Chatbot asks me for personal information.			0.807	
PC3: I am concerned that the AI banking Chatbot is collecting too much personal information about me.			0.821	
Compatibility	**0.91**	**0.78**		(Meuter et al., 2005)
COM1: Using the AI banking Chatbot is compatible with all aspects of my lifestyle.			0.854	
COM2: The AI banking Chatbot fits well with the way I like to get things done.			0.896	

COM3: Using the AI banking Chatbot is completely compatible with my needs.			0.893	
Percieved risk	**0.8**	**0.58**		(Silva et al., 2023)
PR1: I do not feel totally safe providing personal private information over the AI banking Chatbot.			0.779	
PR2: I am worried about using the AI banking Chatbot because other people may be able to access my account.			0.724	
PR3: I do not feel secure sending sensitive information across the AI banking Chatbot.			0.789	
Perceived ease of use	**0.87**	**0.78**		(Ashfaq et al., 2020)
PEU3: I find it easy to get the AI banking Chatbot to do what I want it to do.			0.877	
PEU4: I find the AI banking Chatbot to be easy to use.			0.887	
Perceived usefulness	**0.93**	**0.77**		(Ashfaq et al., 2020)
PU1: I find the AI banking Chatbot useful in my daily life.			0.87	
PU2: Using the AI banking Chatbot helps me accomplish things more quickly.			0.879	
PU3: Using the AI banking Chatbot increases my productivity.			0.856	
PU4: Using the AI banking Chatbot helps me perform many things more conveniently.			0.899	
Trust in AI	**0.87**	**0.7**		(Cheng et al., 2022)
TR2: The AI banking Chatbot is capable of addressing my issues			0.867	
TR3: The AI banking Chatbot’s behavior and response can meet my expectations			0.889	
TR4: I trust the suggestions and decisions provided by the AI banking Chatbot			0.738	
Perceived interactivity	**0.81**	**0.6**		(Cho et al., 2019)
PI1: I can be in control of my personal needs through the AI banking Chatbot			0.743	
PI2: The AI banking Chatbot provides an opportunity for me to give my response			0.778	
PI3: The AI banking Chatbot has the ability to respond to my specific requests quickly and efficiently			0.793	
Social influence	**0.91**	**0.79**		
SI1: People who are important to me think that I should use the AI banking Chatbot in services			0.855	

SI2: People who influence my behavior think that I should use the AI banking Chatbot in services.			0.934	(Balakrishnan et al., 2022)
SI3: People whose opinions I value prefer that I use the AI banking Chatbot in services.			0.867	
Behavioral intention to use	**0.92**	**0.81**		(Venkatesh et al., 2012)
BIU1: I intend to continue using the AI banking Chatbot in the future			0.874	
BIU2: I will always try to use the AI banking Chatbot.			0.93	
BIU3: I plan to use the AI banking Chatbot			0.89	

**The constructs PEU1, PEU2, PC4, and TR1 had to be removed because the criteria were not met*

Table 3. Discriminant validity

	PC	PR	PEU	PU	TR	PI	SI	COM	BIU
PC	-								
PR	**0.89**	-							
PEU	0.28	0.13	-						
PU	0.18	0.07	0.78	-					
TR	0.28	0.17	0.72	0.75	-				
PI	0.21	0.15	0.78	0.79	**0.85**	-			
SI	0.27	0.21	0.55	0.59	0.64	0.55	-		
COM	0.30	0.16	0.71	0.83	0.78	**0.85**	0.74	-	
BIU	0.23	0.17	0.65	0.78	0.68	0.74	0.59	0.81	-

TR=trust in AI, BIU= behavioral intention to use, PR=perceived risk, PU=perceived usefulness, PEU=perceived ease of use, COM=compatibility, SI=social influence, PI= perceived interactivity, PC= privacy concern, ANT=anthropomorphism

As shown in **Table 3**, we find three construct pairs that equal and exceed the acceptability threshold (HTMT>0.85). Those pairs have privacy concern & perceived risk (HTMT 0.89), and trust in AI & perceived interactivity (HTMT = 0.85), and perceived interactivity & compatibility (HTMT=0.85). This indicates potential overlap and suggests that these constructs may not be entirely distinct.

4. Results

4.1 Test of the structural model

To test the hypotheses, we used structural equation modeling (SEM) and mediation analysis using RStudio. Based on common fit indices, the structural model achieved a good fit (see **Table 4**): RMSEA <0.08, CFI, TLI>0.90.

Table 4. Fit Indices

χ^2	df	RMSEA	CFI	TLI
612.652	330.000	0.061	0.944	0.936

4.2 Result of the structural equation model

The results of the SEM are shown in **Table 5** and are discussed below in relation to the hypotheses. H1 proposed that trust in AI (TR) positively influences behavioral intention to use (BIU), and the result ($\beta = 0.111$, $p < 0.168$), which was not statistically significant. Thus, H1 is rejected. This means that while a user may trust AI, it does not mean that the user has a strong behavioral intention to use an AI banking Chatbot. Regarding, H2 proposed that perceived risk (PR) negatively impacts Behavioral Intention to use. However, the statistical result ($\beta = -0.040$, $p < 0.405$) does not support this relationship, and H2 is rejected. This indicates that in the context of an AI banking Chatbot, perceived risk may not be a primary deterrent for users. In contrast, H3, which proposed that perceived usefulness positively affects behavioral intention to use, is strongly supported ($\beta = 0.608$, $p < 0.001$). Surprisingly, H4, which hypothesized a positive relationship between perceived ease of use (PEU) and behavioral intention to use (BIU), is rejected ($\beta = 0.058$, $p < 0.431$). The result suggests that, in this case, usefulness outweighs ease of use as a determinant of adoption, despite ease of use often being considered an important factor in TAM (Davis, 1989). Next, both H5a and H5b, which explored the effect of compatibility (COM) on perceived ease of use and perceived usefulness, respectively, are strongly supported. Compatibility positively affects PEU ($\beta = 0.930$, $p < 0.001$) and PU ($\beta = 1.035$, $p < 0.001$). Regarding H6a and H6b proposed that social influence (SI) positively affects perceived usefulness and behavioral intention to use. As a result, H6b is statistically significant between social influence and behavioral intention to use ($\beta = 0.144$, $p < 0.047$), leading to support of H6a hypotheses. However, the relationship between social influence and perceived usefulness (β = -0.112, $p < 0.131$) is statistically insignificant, leading to rejection of H6a hypotheses. Moreover, H7, which proposed that perceived interactivity (PI) positively impacts trust in AI, is supported (β = 1.121, $p < 0.001$). This signifies that interactive AI banking Chatbot designs help establish trust with users. In contrast, H8 proposed that privacy concern (PC) negatively impacts trust in AI. The effect was rejected (β = -0.036, $p < 0.450$). This indicates that users' concerns over how their personal data is handled by an AI banking chatbot may not strongly influence their level of trust. Similarly, H9, which assumed that anthropomorphism would positively influence TR, is rejected by the data (β = 0.070, $p < 0.512$). The results here imply that humanlike features in AI banking Chatbot may not significantly affect users' trust.

Table 5. Table of coefficients

Relationships	β	*p*	Hypotheses
H1: TR → BIU	0.111	< 0.168	Rejected
H2: PR → BIU	-0.040	< 0.405	Rejected
H3: PU → BIU	0.608	< 0.001	Supported
H4: PEU → BIU	0.058	< 0.431	Rejected
H5a: COM → PEU	0.930	<0.001	Supported
H5b: COM → PU	1.035	<0.001	Supported
H6a: SI → PU	-0.112	<0.131	Rejected
H6b: SI → BIU	0.144	<0.047	Supported
H7: PI → TR	1.121	<0.001	Supported
H8: PC → TR	-0.036	<0.450	Rejected
H9: ANT → TR	0.070	<0.512	Rejected

Note: *TR=trust in AI, BIU= behavioral intention to use, PR=perceived risk, PU=perceived usefulness, PEU=perceived ease of use, COM=compatibility, SI=social influence, PI=perceived interactivity, PC= privacy concern, ANT=anthropomorphism*

4.3 Mediation analysis

We conducted a mediation analysis with 5000 bootstrap samples to study the indirect effect that might have. Specifically, we tested one mediating relationship. The analysis revealed a significant indirect effect running from compatibility to behavioral intention to use via perceived usefulness (β = 0.325, $p < 0.001$, 95% CI [0.187; 0.477]). This finding supports the theory that users who perceive AI banking Chatbot as compatible with their lifestyle and needs are more likely to view them as useful, which in turn drives their intention to use them.

Table 6. Results of the mediation analysis

Mediation	β	95% confidence interval		Significant
		Lower	Upper	
COM → PU → BIU	0.325	0.187	0.477	Yes

4.4 Mean Comparison

We analyzed the effect of the control variable gender on the adoption of AI banking Chatbot in Cambodia. We use One-way ANOVA to assess the impact of Cambodian's gender on their intention to use the AI banking Chatbot. The results reveal no significant difference between male, female, and prefer not to say ($p>0.05$). The mean value of male ($M_{male}=4.84$, $SD=1.367$), female ($M_{female}=4.59$, $SD=1.377$) and prefer not to say ($M_{pns}=4.61$, $SD=0.612$).

5.Discussion

5.1 Discussion of results and theoretical contribution

This study investigates the factors influencing the intention to use of AI banking Chatbot in Cambodia based on the conceptual model developed from TAM (Davis, 1989) as a fundamental model, extended by the combination of one construct from UTAUT (Venkatesh et al., 2003) and from IDT (Rogers, 2003), along with other complementary variables. The results of this study provide insights into the relationship between key constructs of perceived ease of use, perceived usefulness, compatibility, trust in AI, perceived risk, privacy concern, perceived interactivity, anthropomorphism, and social influence. In addition, the results from the structural equation modeling (SEM) and mediation analysis revealed several important insights that both confirm and challenge prior findings, while also offering new contributions to the literature on technology adoption in Cambodia.

Firstly, perceived usefulness emerged as the most significant determinant of behavioral intention to use an AI banking Chatbot. This strong effect of perceived usefulness on behavioral intention supports TAM (Davis, 1989), confirming that users adopt technology primarily when that technology delivers a clear functional benefit. This finding is aligned with prior studies in chatbots (Gopinath & Kasilingam, 2023) and indicates that Cambodians prioritize tangible benefits such as efficiency, productivity, and convenience when deciding whether to engage with an AI banking Chatbot. In contrast, perceived ease of use did not significantly influence behavioral intention to use, which is contrary to TAM's finding (Davis, 1989) and another prior study (Gopinath & Kasilingam, 2023; D. Zhang & Zhao, 2024). This suggests that in contexts where digital literacy is rising and mobile banking has become commonplace, perceived ease of use may be taken for granted, and users instead focus on whether the technology provides meaningful utility. Secondly, the findings show compatibility as an important driver of both perceived usefulness and perceived ease of use, aligning with prior studies (Koenig-Lewis et al., 2010). Tailored to the case of an AI banking Chatbot, it aligns with user lifestyles, needs, and practices, they are more likely to be perceived as both useful and easy to use. The mediation analysis further demonstrated that compatibility indirectly drives behavioral intention to use through perceived usefulness. This reinforces the idea that for emerging markets like Cambodia, technology adoption, specifically tailoring it to the intention to use of AI banking Chatbot, depends heavily on compatibility. Thirdly, trust in AI and perceived risk did not significantly affect behavioral intention to use, which is contrary to prior studies (Abikari, 2024; Chauhan et al., 2022; Liu & Tao, 2022; Silva et al., 2023). Similarly, privacy concern and anthropomorphism did not significantly influence trust in AI. One explanation may be that Cambodian consumers already place high baseline trust in banking institutions, and their limited awareness of AI-related risks reduces the salience of these constructs. Surprisingly, the study found that social influence did not significantly impact perceived usefulness but did have a significant impact on behavioral intention to use (Venkatesh et al., 2003). In the context of AI chatbot adoption in Cambodian banks, the finding suggests that while social influence, such as recommendations from colleagues, friends, or family, does not significantly shape users' perceptions of the usefulness of AI chatbots. But it does play a critical role in their behavioral intention to use these technologies. This means that Cambodian users are likely to adopt AI banking chatbots if they are influenced by people in their social or professional circles, even if they are not yet convinced of the chatbots' usefulness. On the other hand, perceived interactivity significantly boosted trust in AI, confirming earlier research that engaging and responsive chatbots shape consumers' trust in AI banking chatbots and their positive impact on trust for users (Cyr et al., 2009). However, since trust in AI itself did not translate into usage intention, this implies that trust may function as a secondary factor in adoption, valued for shaping perceptions but insufficient to drive behavioral intention alone.

5.2 Managerial recommendations

Our research provides actionable insight for banking institutions in Cambodia seeking to design, implement, and promote AI Chatbots. The findings give managers practical guidance that can be used to adapt their artificial intelligence strategies become better effectively with consumer expectations and use for both immediate action as well as long-term strategic action.

For immediate priorities, we recommend that managers strongly focus on perceived usefulness as the core driver of adoption. Cambodian consumers are motivated by clear functional benefits such as time savings, convenience, and productivity. Banks should therefore design chatbots that go beyond answering frequently asked questions FAQs and deliver high-value services like transaction processing, loan applications, and personalized financial advice. Marketing communications should also highlight these tangible benefits, as it is a key attraction for Cambodians to use AI banking Chatbot. Secondly, the manager should ensure compatibility with existing customer behaviors. Since compatibility strongly influences both perceived usefulness and ease of use, banks must align chatbots with existing practices. That could be integrating with popular mobile payment systems like Bakong (Cambodia's national digital currency platform), supporting Khmer as the default language, and offering simple, culturally appropriate interfaces. Thirdly, since social influence significantly impacts behavioral intention, banks should actively encourage peer recommendations and endorsements. This can include promoting testimonials from satisfied customers, highlighting social proof on digital platforms, encouraging influencers or respected community figures to share their experiences, and implementing referral programs where users benefit from introducing others to the chatbot. Banks should creating a sense of community or social validation around chatbot use can significantly boost adoption. Additionally, managers should also prioritize interactivity. While perceived interactivity did not directly increase usage intention, it strongly boosted trust. Chatbots should provide quick, context-aware responses and adapt to user input. This will enhance the customer experience and indirectly support adoption.

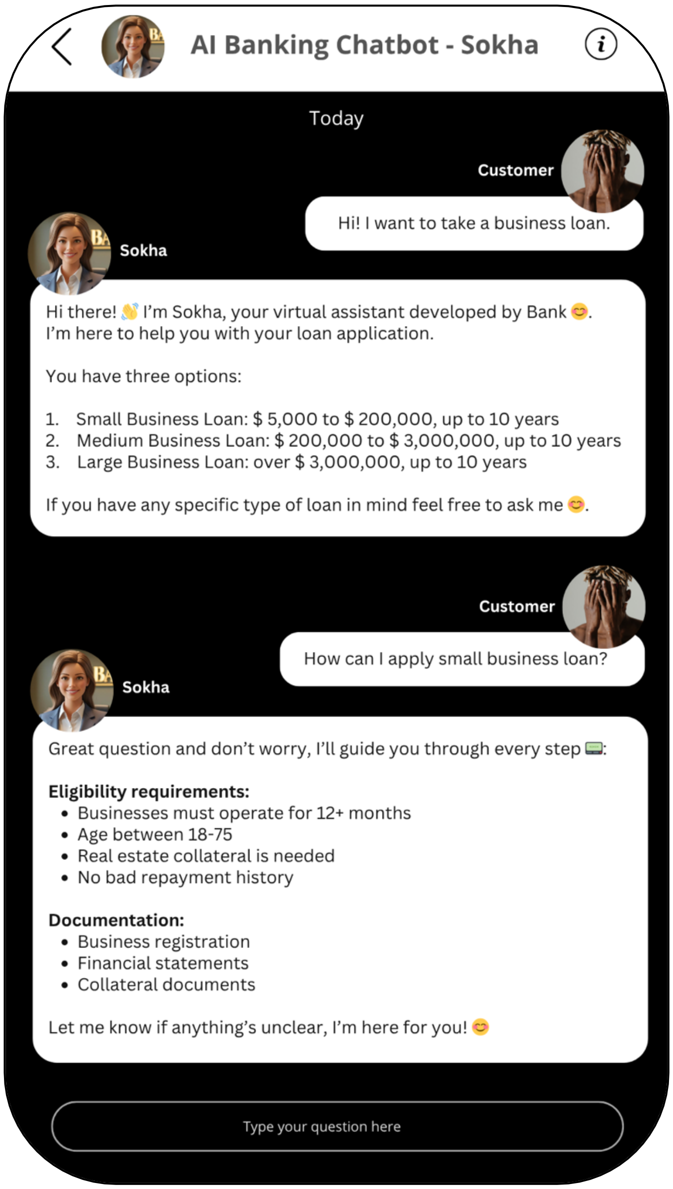
For long-term strategic actions, developers should consider adding a voice-based feature to AI Chatbot, allowing users to send voice notes as an extra function, besides typing messages in Khmer, as many young people prefer to write Khmer using the Latin alphabet. Additionally, a voice-input option would provide substantial benefits for older users who may face difficulties with typing, thereby enabling them to engage more easily with AI banking Chatbot services. In addition, even though trust in AI did not significantly predict adoption in this study, maintaining transparency, safeguarding user data, and ensuring consistent chatbot performance will be vital for long-term acceptance as consumers become more aware of AI-related risks. Lastly, managers should leverage customer feedback loops. Banks should invest in systems that continuously collect, analyze, and act on user feedback to improve chatbot services, ensuring that adoption remains sustainable over time. In addition, banks should consider strengthening their in-house expertise or recruiting AI and data specialists to analyze consumer data with greater precision.

5.3 Limitations and future research directions

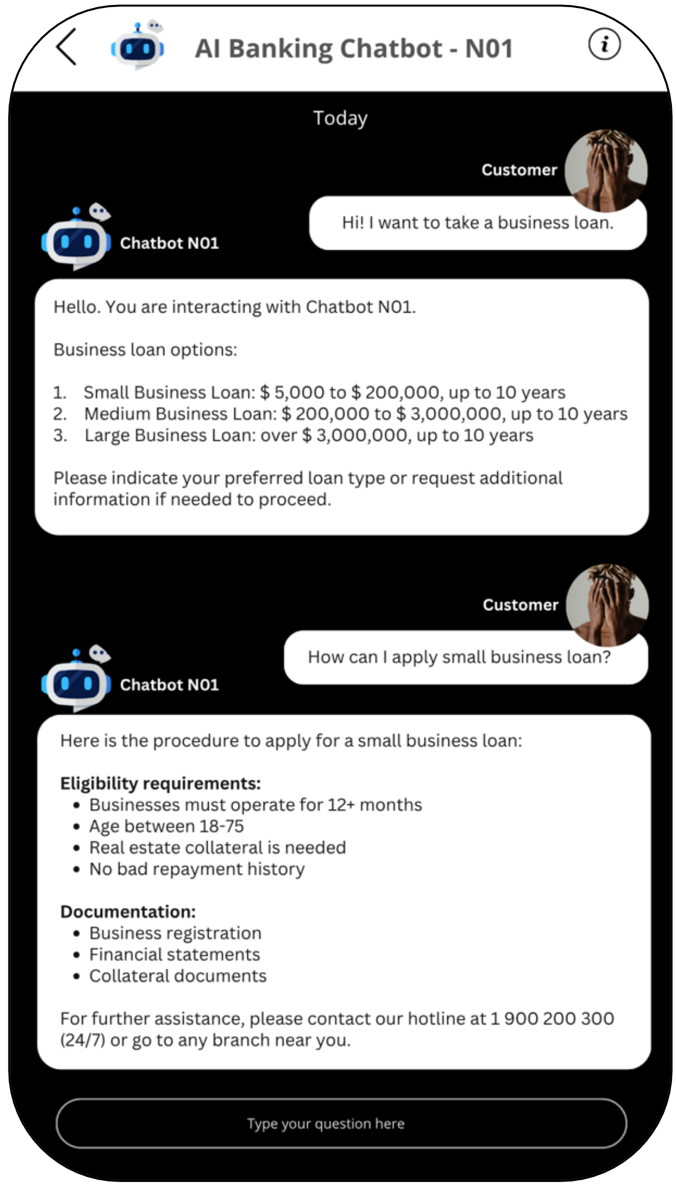
First, the sample of this study may limit the generalizability of the findings. The majority of respondents were relatively young and highly educated, which may not reflect the views of older or less digitally literate segments of the Cambodian population. Since digital adoption attitudes often differ by age, education, and socioeconomic background, the results may overrepresent the perspectives of digitally active individuals. Second, there is a limitation on measurement validity. The HTMT analysis indicated potential overlap between certain constructs, such as privacy concern with perceived risk, trust in AI with perceived interactivity, and perceived interactivity with compatibility. This suggests that Cambodian consumers may not perceive these dimensions as clearly distinct. Third, while the study integrated constructs from TAM, UTAUT, and IDT, some potentially influential variables were not analyzed. For example, factors such as service quality and customer satisfaction may also influence AI banking Chatbot adoption. In addition, the manipulation of anthropomorphism did not produce the intended effect, which limits conclusions regarding its role in shaping user trust. Finally, this study relied on self-reported perceptions and intentions rather than actual behavioral data. Although behavioral intention is a strong predictor of technology usage, it does not always translate into real adoption.

Building on these limitations, several directions for future research are suggested. First, future studies should include broader and more diverse samples, particularly targeting provincial populations, older age groups, and less digitally literate users, to provide a more comprehensive understanding of AI banking Chatbot adoption across Cambodian society. Second, future researchers should incorporate attention-check questions within the questionnaire and exclude responses from participants who fail to answer them correctly. Moreover, they should consider reducing the number of questions to minimize respondent fatigue and prevent confusion. Additionally, selecting a model with more clearly defined concepts would help avoid ambiguity and improve the reliability of the findings. Third, future research could extend the conceptual model by incorporating additional variables, such as service quality or customer satisfaction, which may provide deeper insight into adoption behaviors in Cambodia. Fourth, future research could also test whether more advanced forms of anthropomorphism exist. For instance, beyond text-based cues such as names or friendly language, future studies could test voice-based interactions. Finally, future work should aim to validate findings using behavioral and transactional data, such as chatbot interaction logs or banking transaction records, to complement self-reported measures. This would provide a more accurate reflection of actual usage patterns and enhance the robustness of adoption models.

Appendix 1: Scenarios



Scenario1: High Anthropomorphism



Scenario 2: Low Anthropomorphism

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