Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Extending Technology Continuance Theory: Investigating the Impact of AI Characteristics on Continuance Intention in AI Enabled Mobile Banking

Shuoteng Huang, Fei Huang
aSSIST University, Seoul, The Republic of Korea, and
aSSIST University, Seoul, The Republic of Korea

ARTICLE INFO	ABSTRACT

Received: 16 Nov 2024
Revised: 20 Dec 2024
Accepted: 15 Jan 2025

Purpose–This study seeks to address the gap in research regarding the influence of artificial intelligence (AI) characteristics on users' continuance intention (CI) within mobile banking contexts. Despite the widespread adoption of AI as a transformative technology in mobile banking, there is limited systematic research employing Technology Continuance Theory (TCT) to examine the effect of AI features on users' CI towards AI-powered mobile banking applications. This research explores the roles of perceived intelligence and perceived anthropomorphism as key AI characteristics and their mechanisms in shaping CI.

Design/methodology/approach–A quantitative methodology, using a cross-sectional survey design, was applied to collect data from 395 mobile banking users via structured questionnaires. Partial least squares structural equation modeling (PLS-SEM) was used to test the hypotheses. The model examines how perceived intelligence and anthropomorphism, mediated by confirmation, perceived usefulness, and perceived ease of use, influence user satisfaction (SAT) and attitudes, which ultimately enhance CI towards mobile banking. Additionally, the moderating effect of technology anxiety on the SAT-CI relationship was also tested.

Findings–The results demonstrate that perceived intelligence and anthropomorphism positively impact users' confirmation, perceived usefulness, and ease of use, thereby strengthening SAT and fostering a positive attitude, which significantly boosts CI towards mobile banking applications. Additionally, perceived usefulness has a direct and substantial effect on CI. Technology anxiety was found to negatively moderate the SAT-CI relationship, with users exhibiting higher anxiety showing a weaker connection between SAT and CI.

Research limitations/implications–The study is limited to a specific geographical area, which may limit the generalizability of the findings. Future research could replicate this study in other regions. Furthermore, the cross-sectional nature of the data restricts causal inferences, suggesting the need for longitudinal studies to validate the model. This research offers novel insights into the role of AI characteristics in influencing CI, which could guide future studies and inform the design of mobile banking services.

Originality/value–This research is one of the first to systematically explore the impact of perceived intelligence and anthropomorphism within the TCT framework in mobile banking. It contributes to the theoretical understanding of mobile banking continuance intention and provides practical guidance for developers of AI-based applications aimed at improving CI and SAT. The findings highlight the importance of AI characteristics in enhancing users' satisfaction and continuance intention in mobile banking.

Keywords: Technology Continuance Theory, Continuance intention, Mobile banking, AI characteristics, Technology anxiety

INTRODUCTION

Mobile banking has become a popular, efficient, and cost-effective alternative banking channel, providing users with 24/7 access to services (Yuan et al., 2016). As a key component of financial technology, mobile banking enhances service accessibility while reducing the physical constraints of traditional banking (Payne et al., 2021). Through mobile banking, customers can quickly and easily perform various financial and non-financial activities, including payments, transfers, and investments. It also allows banks to reduce operational pressure on physical branches and significantly lower costs (Banerjee and Sreejesh, 2022). For customers, mobile banking offers functions such as bill payments, online shopping, money transfers, and account statement generation, thus delivering a seamless and comprehensive banking experience. This reduces banks' operating expenses and strengthens their competitive positioning in the market (Nguyen et al., 2022).

In recent years, artificial intelligence (AI) has become a pivotal feature in mobile banking applications (Lee et al., 2023). AI, which involves computer simulations of human intelligence, allows machines to perform tasks or offer services that benefit users and organizations in various sectors (Doumpos et al., 2023). The incorporation of AI has transformed traditional mobile banking into intelligent mobile banking, addressing the demand for personalized, smart services that improve the overall user experience (Lin et al., 2023). By mimicking human cognitive functions, AI has become integral to mobile banking apps, adapting to user and business needs in diverse contexts (Huang and Rust, 2020). This transition from traditional banking to intelligent systems facilitates more tailored interactions with users, significantly boosting their satisfaction and engagement (Payne et al., 2021). For instance, some mobile applications feature AI-powered customer service systems using

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

anthropomorphic avatars and human-like communication to better understand user intent and improve operational efficiency (Lee and Chen, 2022).

While numerous studies have focused on the pre-adoption behaviors of mobile banking users (Koksal, 2016; Tran and Corner, 2016; Farah et al., 2018; Elhajjar and Ouaida, 2019; Shams et al., 2020), continuance intention has emerged as a key factor for the sustained success of mobile banking apps (Banerjee and Sreejesh, 2022). Continuance intention refers to the "user's intention to continue using an already adopted mobile banking technology" (Yuan et al., 2016). Research indicates that continuance intention is more critical than initial adoption for ensuring the long-term success of mobile banking applications (Kumar et al., 2018). To explain this phenomenon, scholars have often employed models such as the Technology Acceptance Model (TAM) (e.g., Yin and Lin, 2022; Kelly et al., 2022) and the Expectation Confirmation Model (ECM) (e.g., Twum et al., 2023; Rahi et al., 2022). Although both models offer valuable insights, they have inherent limitations. To address these, the Technology Continuance Theory (TCT) was developed as an integrated model that provides a more comprehensive explanation of continuance behaviors (Liao et al., 2009). This model has been validated by several studies for revealing deeper insights into user behavior that cannot be fully explained by a single theory (Foroughi et al., 2019; Ahayer and Bao, 2019; Rahi et al., 2021; Aprilia and Amalia, 2023).

Recent research suggests that AI characteristics significantly influence users' decisions to adopt AI-based applications (Balakrishnan and Dwivedi, 2021; Moussawi et al., 2022; Pillai and Sivathanu, 2020). Within mobile banking, AI is widely used to enhance functionality and improve the user experience. Literature indicates that, unlike traditional systems, AI's defining features—intelligence and anthropomorphism—are key in shaping user perceptions (Balakrishnan and Dwivedi, 2021; Moussawi et al., 2022). In the context of mobile banking, intelligence is evident in AI-powered applications' ability to perform tasks autonomously, thus simplifying services and transactions. Anthropomorphism refers to AI systems' human-like interactions with users, which help facilitate various tasks (Lin and Lee, 2023). As AI-driven mobile banking applications increasingly replace traditionally human-centered services, technology anxiety has emerged as a critical factor. Users may experience anxiety due to the complexity or unpredictability of AI systems, potentially moderating their decision to continue using these services. Hence, studying the role of technology anxiety as a moderating factor provides a more comprehensive understanding of user decisions regarding AI mobile banking apps (Li and Huang, 2020).

Therefore, the transformation of traditional mobile banking into AI-enhanced applications presents new challenges. Technology Continuance Theory (TCT) is a foundational framework for explaining users' continuance intention in mobile banking, offering more robust explanatory power than traditional models. However, the specific effects of AI characteristics—intelligence and anthropomorphism—on TCT remain underexplored, warranting further research and empirical investigation. This leads to a critical research question: Do intelligence and anthropomorphism

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

influence users' continuance intention toward mobile banking apps via the mechanisms outlined by TCT? If so, how?

This study aims to examine how perceived intelligence and anthropomorphism affect users' confirmation, perceived usefulness, perceived ease of use, satisfaction, attitude, and continuance intention with AI-enabled mobile banking apps. A questionnaire survey collected 395 valid responses, and Partial Least Squares Structural Equation Modeling (PLS-SEM) was used for hypothesis testing. Additionally, the moderating effect of technology anxiety on the relationship between satisfaction and continuance intention was explored. By integrating intelligence and anthropomorphism into the TCT framework, this study unveils the mechanisms through which AI characteristics influence confirmation, perceived usefulness, perceived ease of use, satisfaction, attitude, and continuance intention. The findings contribute new insights to the literature, enhancing the applicability and explanatory power of TCT and offering a more effective framework for predicting and explaining users' continuance behaviors in AI-enabled mobile banking environments.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Technology continuance theory (TCT)

The Technology Continuance Theory (TCT) integrates key components from the Technology Acceptance Model (TAM), Cognitive Model (COG), and Expectation Confirmation Model (ECM) to provide a thorough framework for understanding users' intentions to persist in using technology (Liao et al., 2009). At its core, TCT combines six fundamental constructs: satisfaction, confirmation, perceived usefulness, attitude, perceived ease of use, and continuance intention, forming a cohesive model that offers a more holistic explanation of users' ongoing engagement with technology (Liao et al., 2009). By merging attitude and satisfaction within a single framework, TCT addresses a broad spectrum of factors influencing users' sustained interaction with technology (Liao et al., 2009).

The Expectation Confirmation Model (ECM), which informs TCT, is based on Oliver's (1980) Expectation Confirmation Theory (ECT) and involves four main variables: confirmation, perceived usefulness, satisfaction, and continuance intention. In this model, confirmation refers to the alignment between users' expectations and the actual performance of the technology (Bhattacherjee, 2001). Perceived usefulness, a concept drawn from TAM, refers to the perceived benefits of using the technology (Bhattacherjee, 2001). Satisfaction reflects the emotional response users have towards their interaction with the technology (Bhattacherjee, 2001; Lee et al., 2023). While both TAM and ECM focus on user adoption and continuance intention, ECM emphasizes post-adoption behaviors, whereas TAM primarily addresses initial acceptance (Aprilia and Amalia, 2023). By integrating these elements, TCT overcomes the limitations of each individual model, offering enhanced predictive and explanatory power regarding users' post-adoption behaviors (Liao et al., 2009; Rahi et al., 2021).

TCT goes beyond the ECM, TAM, and COG in terms of both applicability and explanatory depth. Pattanayak et al. (2017) emphasize that TCT places greater importance on users' long-term engagement with technology, rather than solely focusing on initial adoption. Several studies in diverse technological settings support TCT's value. For instance, Alraimi et al. (2015), Hoehle et al. (2012), and Lin (2012) empirically tested TCT's constructs. Lin (2012) found that in online learning environments, satisfaction and perceived fit were critical for continuance intention, while Alraimi et al. (2015) identified that perceived usefulness and satisfaction significantly influenced continuance intention in similar contexts. In internet banking, Hoehle et al. (2012) highlighted that perceived usefulness and confirmation were key in determining satisfaction and continuance intention, especially when trust was maintained. Additionally, Foroughi et al. (2019) confirmed the relevance of TCT's factors in mobile banking, demonstrating their significant impact on users' decisions to continue using mobile banking services.

These studies collectively reinforce the strength of TCT: its ability to offer a more comprehensive understanding of user behavior across various technological contexts by integrating multiple factors. TCT's holistic perspective makes it a robust framework for examining continuance behaviors in various domains, including mobile banking, where understanding sustained use is crucial for both theoretical and practical insights.

The TCT and continuance intention towards AI mobile banking apps

Although research on Technology Continuance Theory (TCT) in mobile banking and related platforms has advanced, studies specifically addressing AI-enabled mobile banking applications remain sparse. Foroughi et al. (2019) examined continuance intention in mobile banking through the TCT framework, highlighting the importance of technological factors in shaping user behavior. However, their research did not consider the role of artificial intelligence in mobile banking. Similarly, Aprilia and Amalia (2023) explored users' continuance intention for mobile wallets by focusing on perceived security within TCT, further validating its applicability to financial services, though their analysis was confined to traditional financial technologies. Khayer and Bao (2019) incorporated context-awareness with TCT to study continuance intention among Alipay users, emphasizing the influence of technology and context on user behavior, but did not address AI-specific elements. Rahi et al. (2021) combined TCT with the Task-Technology Fit (TTF) theory to explore continuance intention in internet banking, reinforcing TCT's effectiveness in explaining user behavior in financial services. These studies highlight TCT's relevance across various fintech platforms, yet fail to explore the specific effects of AI-enabled systems.

The integration of artificial intelligence in mobile banking has notably transformed user experiences, especially through its intelligent and anthropomorphic features (Lee and Chen, 2022; Lin et al., 2023). These characteristics not only enhance system interactivity but also shape user perceptions, particularly regarding the fulfillment of their needs and overall experience. In this context, the present study incorporates intelligence and anthropomorphism as antecedent variables within the TCT framework, aiming to investigate how these AI traits influence users' continuance intention toward AI-powered mobile banking applications. By integrating these AI-specific features, the study addresses a gap in the existing literature and expands TCT's explanatory power in the context of AI-driven financial technology.

Given that TCT serves as the foundational model, we first validated the hypothesized relationships within TCT in the setting of AI-enabled mobile banking.

Confirmation of AI-enabled mobile banking towards satisfaction & perceived usefulness

In the information systems (IS) literature, a significant association between users' expectation confirmation and their satisfaction with a technology is widely supported (Bhattacherjee, 2001; Hoehle et al., 2012). Hoehle et al. (2012) demonstrated that expectation confirmation fosters a positive attitude among internet users, thereby enhancing satisfaction. Similarly, Zhang et al. (2015) validated the substantial impact of expectation confirmation on satisfaction in the context of website continuance by combining the Expectation Confirmation Model (ECM) with the Theory of Planned Behavior. Foroughi et al. (2019) further revealed a direct relationship between expectation confirmation and perceived usefulness, indicating that expectation confirmation not only influences satisfaction but also plays a critical role in shaping perceived usefulness. In e-finance, Zhou et al. (2018) confirmed that expectation confirmation significantly impacts user satisfaction and their intention to continue using e-financial services. Consistent across literature, expectation confirmation and perceived usefulness significantly influence continuance intention toward technologies (Albuhisi and Abdallah, 2018; Bhattacherjee, 2001; Hoehle et al., 2012; Liao et al., 2009; Zhou et al., 2018).

Satisfaction is defined as "a positive emotional state resulting from an evaluation of the performance of a product or service based on past purchase and usage experience" (Szymanski and Henard, 2001). According to ECM, expectation confirmation with mobile banking services can significantly enhance user satisfaction, whereas unmet expectations may lead to dissatisfaction and discontinuance intention (Fu et al., 2018; Peng et al., 2019). For instance, Susanto et al. (2016) showed in their study on smartphone banking that users' confirmation experience after initial use significantly impacts their satisfaction.

Beyond its influence on satisfaction, confirmation can adjust users' perceptions of an IS's usefulness, particularly when initial expectations are unclear (Tsai et al., 2014). In such cases, customers may perceive fewer benefits from the technology due to uncertainty; however, once their expectations are confirmed through actual usage, perceived usefulness may increase. Conversely, if expectations are unmet, perceived usefulness may decrease. Multiple studies support this notion, indicating that confirmation can enhance perceived usefulness, whereas a lack of confirmation may lead to its decline (Mou et al., 2017; Sarkar and Khare, 2018). Based on this discussion, the following hypotheses are proposed:

H1. Confirmation has a positive effect on satisfaction.

H2. Confirmation has a positive effect on perceived usefulness.

Perceived easy of use of AI-enabled mobile banking towards attitude & perceived usefulness

Perceived ease of use (PEU) refers to an individual's evaluation of the cognitive effort required to

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

operate a technology (Davis, 1989; Zailani et al., 2015). Previous studies consistently show that PEU positively influences users' attitudes toward mobile banking services, supporting the Theory of Reasoned Action (TRA) (Chitungo and Munongo, 2013; Munoz-Leiva et al., 2017). PEU is also identified as a key factor in determining perceived usefulness in mobile shopping (Natarajan et al., 2018) and online shopping contexts (Pengnate and Sarathy, 2017). Foroughi et al. (2019) found that PEU significantly affects users' attitudes toward continued mobile banking use. Likewise, Humbani and Wiese (2019) highlighted the strong connection between PEU and perceived usefulness, confirming its impact on mobile payment app users' perceptions. Building on these theoretical perspectives and empirical findings, the following hypotheses are proposed:

H3. Perceived ease of use has a positive effect on attitudes.

H4. Perceived ease of use has a positive effect on perceived usefulness.

Perceived usefulness of AI-enabled mobile banking towards satisfaction,attitude & continuance intention

In the Technology Acceptance Model (TAM), Davis et al. (1989) established the link between perceived usefulness (PU) and user attitude. Liao et al. (2009) later expanded on this, showing that both PU and perceived ease of use significantly influence users' continuance intention. Numerous studies have corroborated this, indicating that PU directly impacts the intention to continue using internet banking (Hoehle et al., 2012; Jabnoun and Hassan Al-Tamimi, 2003). PU is defined as an individual's perception of how technology improves their performance (Rauniar et al., 2014), and it has been recognized as a strong predictor of behavioral intention across various domains, including internet banking (Martins et al., 2014), online usage (Mou et al., 2017), mobile commerce (Shaw and Sergueeva, 2019), and healthcare (Gilani et al., 2017). The positive relationship between user satisfaction and PU has been well-documented (Kumar et al., 2018; Lim et al., 2019; Rezvani et al., 2017), and PU plays a central role in shaping users' attitudes and intentions toward mobile banking services (Shaikh and Karjaluoto, 2015). For instance, Alraimi et al. (2015) demonstrated that PU and user satisfaction significantly influence continuance intention in online learning, while Hoehle et al. (2012) highlighted the role of PU, expectation confirmation, and continuance intention in customer satisfaction. These findings suggest that when users perceive high PU in mobile banking services, their attitude and intention to continue using the service are positively impacted. Based on these insights, the following hypotheses are proposed:

H5. Perceived usefulness has a positive effect on satisfaction.

H6. Perceived usefulness has a positive effect on attitude.

H7. Perceived usefulness has a positive effect on continuance intention.

Satisfaction of AI-enabled mobile banking towards continuance intention

In the Expectation Confirmation Model (ECM), Bhattacherjee (2001) argues that user satisfaction, derived from prior usage experiences, plays a crucial role in determining the intention to continue using an information system. This aligns with marketing studies that show customer satisfaction is a key driver of repeat purchases, a concept similarly applicable to the continued use of information technology (Tran et al., 2019). Research consistently demonstrates that user satisfaction positively influences continuance intention in various mobile technologies, including mobile banking (Yuan et al., 2016), mobile social networks (Hsu and Lin, 2018), and mobile shopping (Shang and Wu, 2017). Ofori et al. (2017) further affirmed the importance of user satisfaction in internet banking, showing its significant impact on continuance intention. Lin (2012) also found that satisfaction positively affects continuance intention in the context of e-learning. In mobile banking, satisfaction arises when users' expectations align with their actual experiences. While satisfaction and attitude are typically treated as distinct concepts, some studies equate them (Gilani et al., 2017). Satisfaction is often viewed as an emotional reaction tied to specific experiences, whereas attitude is a broader, more enduring evaluation of a service or product (Taylor and Todd, 1995; Venkatesh and Davis, 2000). Several studies suggest that user satisfaction has a positive influence on attitudes toward technology (Iranmanesh et al., 2017; Yang et al., 2017). Based on these insights, the following hypotheses are proposed:

H8. Satisfaction has a positive effect on continuance intention.

H9. Satisfaction has a positive effect on attitude.

Attitude of AI-enabled mobile banking towards continuance intention

The Technology Acceptance Model (TAM) posits that attitude plays a critical role in determining users' intention to continue using a technology. Davis (1989) defines attitude as the degree of an individual's positive or negative feelings toward performing a particular behavior. A wealth of research has supported the positive relationship between attitude and continuance intention. Studies by Hamari and Koivisto (2015), Manser Payne et al. (2018), and Wu and Chen (2017) demonstrate that attitude significantly influences users' intention to keep using technology. Similarly, Foroughi et al. (2019) found that attitudes impact continuance intention in e-banking, while Liao et al. (2009) highlighted that a positive attitude enhances users' willingness to continue using technology. Consequently, attitude is recognized as a pivotal factor in predicting continuance intention in mobile banking. Based on this, the following hypothesis is proposed:

H10. Attitude has a positive effect on continuance intention.

Perceived intelligence of AI-enabled mobile banking towards confirmation,perceived usefulness & perceived easy of use

Artificial intelligence (AI) integrates digital processing algorithms with speech and text recognition, enabling effective communication with users and facilitating data collection. This capability enables AI to swiftly comprehend user needs and assist in task completion (Moussawi et al., 2022). In this context, perceived intelligence refers to users' perception of AI's capabilities during interactions (Balakrishnan and Dwivedi, 2021). Within mobile banking, when users perceive AI as intelligent, they are more likely to trust its ability to efficiently solve problems, thereby enhancing the delivery of banking and financial services (Lee et al., 2023). For instance, AI can provide multiple solutions to user inquiries through keyword recognition or offer personalized wealth management product recommendations based on users' risk profiles and income (Lin and Lee, 2023). The intelligence of AI improves service maturity by enhancing semantic understanding and task processing efficiency, thereby enriching the overall user experience (Sun et al., 2021).

Moreover, perceived intelligence can further boost perceived usefulness through user confirmation. When users see that AI meets their financial needs, their trust in the application grows, reinforcing the belief that the service aligns with their expectations (Bhatnagr et al., 2024). This confirmation builds users' confidence in AI-enabled mobile banking, fostering the belief that AI can effectively address operational issues and complete tasks efficiently (Lee and Chen, 2022). Additionally, AI's intelligence reduces the cognitive effort required by users, thereby improving perceived ease of use and strengthening their intention to continue using the application. Previous research indicates that AI's intelligent features are positively linked to users' perceptions of performance benefits, enhancing their sense of efficiency and task completion (Moussawi et al., 2022; Lin et al., 2023). Based on this, the following hypotheses are proposed:

H11a. Perceived intelligence has a positive effect on confirmation.

H11b. Perceived intelligence has a positive effect on perceived usefulness.

H11c. Perceived intelligence has a positive effect on perceived ease of use.

Perceived anthropomorphism of AI-enabled mobile banking towards confirmation,perceived usefulness & perceived easy of use

A notable characteristic of AI is anthropomorphism, which is prevalent in AI-powered mobile banking applications (Lee et al., 2023; Lin et al., 2023). Anthropomorphism enables AI to express emotions during interactions, offering users a more human-like service experience (Moussawi et al., 2020). This human-like quality can evoke positive emotions, influencing users' attitudes and perceptions, and significantly enhancing their overall experience (Lee et al., 2023; Balakrishnan and Dwivedi, 2021). By establishing an emotional bond, AI-enabled mobile banking applications not only foster trust but also strengthen the connection between users and the AI system (Lee and Chen, 2022). For instance, AI can analyze users' financial needs and respond with expressions of care, such as friendly text or imagery, enhancing emotional engagement (Moussawi et al., 2022). These anthropomorphic interactions create a sense of warmth, encouraging deeper user involvement with the application (Lee and Chen, 2022), which in turn influences their assessment of whether the service meets their expectations.

Moreover, anthropomorphism facilitates more intuitive communication, making mobile banking applications easier to use and improving perceived ease of use. By mimicking human-like conversation, AI supports users in managing complex tasks or transactions, akin to face-to-face interactions (Lee et al., 2023; Lin et al., 2023). This conversational ease reduces cognitive effort, boosting users' intention to engage with the application. Additionally, anthropomorphism enhances user trust in AI, helping them handle financial transactions more effectively and boosting perceived usefulness (Lee and Chen, 2022; Lin et al., 2023). When users perceive AI-enabled mobile banking systems as capable of addressing their needs in a flexible, human-like manner, they are more likely to regard the technology as essential in achieving their financial objectives. Studies indicate that anthropomorphic features improve users' ability to interact with AI-based banking applications and address their financial requirements (Lee et al., 2023; Lee and Chen, 2022; Lin et al., 2023). Based on these insights, the following hypotheses are proposed:

H12a. Perceived anthropomorphism has a positive effect on confirmation.

H12b. Perceived anthropomorphism has a positive effect on perceived usefulness.

H12c. Perceived anthropomorphism has a positive effect on perceived ease of use.

Moderating role of Technology anxiety of AI-enabled mobile banking on satisfaction & continuance intention

Technology anxiety refers to the discomfort or unease users experience when interacting with certain technologies (Maduku et al., 2023). This anxiety often arises from unfamiliarity with emerging technologies, such as AI-enabled mobile banking applications, as well as the perceived complexity in using them (Pham et al., 2024). In this study, we propose that technology anxiety moderates the relationship between user satisfaction and continuance intention. Specifically, in the context of AI-enabled mobile banking, anxiety acts as a critical moderating factor, as the intelligence and anthropomorphic elements of AI may induce uncertainty or stress in some users (Li and Huang, 2020). Understanding technology anxiety is crucial for comprehensively evaluating users' reactions to AI characteristics, such as intelligence and anthropomorphism.

We selected technology anxiety as a moderating variable due to its potential influence on users' cognitive and behavioral responses, particularly regarding perceived usefulness and continuance intention (Maduku et al., 2023). Previous studies suggest that anxiety may intensify during cognitive and decision-making processes, especially when users interact with complex AI systems. In the case of AI-enabled mobile banking, technology anxiety is expected to moderate the relationship between satisfaction and continuance intention. We hypothesize that users with lower technology anxiety will exhibit a stronger positive correlation between satisfaction and their intention to continue using AI-driven mobile banking applications. Conversely, users with higher anxiety levels may show a weaker link between satisfaction and continuance intention, as the perceived complexity or uncertainty of the technology may lead to negative emotions.

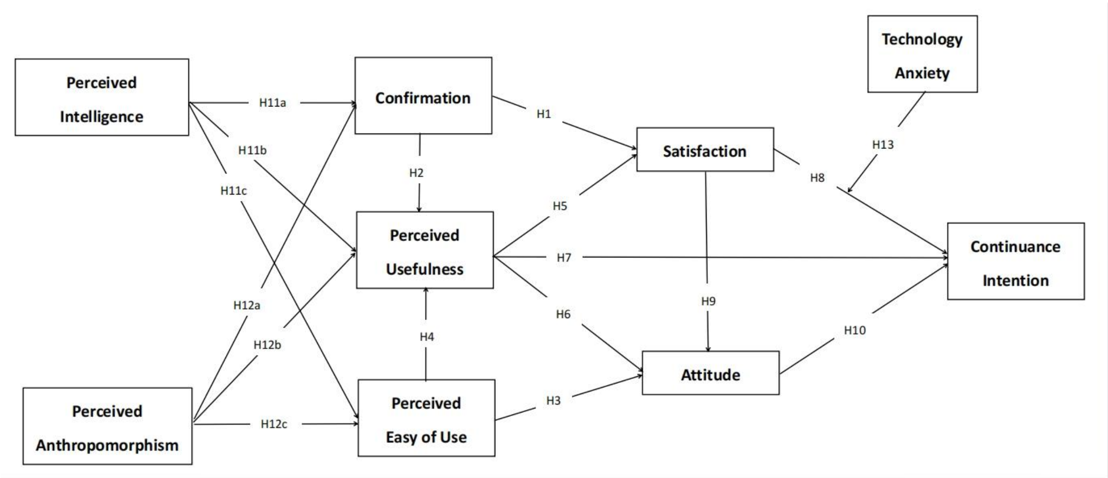
Technology anxiety can act as a psychological barrier, influencing users' perceptions and experiences with AI-enabled mobile banking applications (Debasa et al., 2023; Rahmani et al., 2023). Users with lower anxiety are more likely to recognize AI's benefits and are less likely to let minor issues interfere with their experience, thereby strengthening the relationship between satisfaction and continuance intention. On the other hand, those with higher anxiety may display more skepticism, diminishing the effect of satisfaction on continuance intention. Based on these insights, the following hypothesis is proposed:

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

H13. Technology anxiety negatively moderates the effect of satisfaction on continuance intention.

This research is based on Technology Continuance Theory (TCT) and explores the influence of AI characteristics, namely perceived intelligence and anthropomorphism, on users' continuance intention toward AI-enabled mobile banking. It also incorporates technology anxiety as a moderating variable to examine its effect on the relationship between user satisfaction and continuance intention. By investigating these AI traits as antecedents and technology anxiety as a moderator, the study seeks to enhance understanding of the factors that influence users' continued engagement with AI-driven mobile banking applications. The research model used in this study is illustrated in Figure 1.

Figure 1. Conceptual Framework



RESEARCH METHODOLOGY

Survey instruments

This study utilized established multi-item scales, widely adopted in prior research, to measure the relevant constructs. The questionnaire consisted of two parts. The first part included scales assessing various dimensions of each construct. Perceived intelligence was measured through responsiveness (2 items), understanding of needs (2 items), and problem-solving ability (2 items), based on Moussawi et al. (2020) and Lee & Chen (2022). Perceived anthropomorphism was assessed with items on warmth (2 items), communication speed (2 items), and competence (2 items), adapted from Lee & Chen (2022) and Malhotra & Ramalingam (2023). The confirmation scale (4 items) was adapted from Bhattacherjee (2001), while perceived usefulness (4 items) was derived from Bhattacherjee (2001) and Venkatesh & Davis (2000). Perceived ease of use (5 items) followed Venkatesh & Davis's (1996, 2000) design, and satisfaction (4 items) was measured using Bhattacherjee's (2001) scale. Attitude (3 items) referenced Schierz et al. (2010) and Pham et al. (2024), while technology anxiety (3 items) used scales from Kang & Namkung (2019) and Pham et al. (2024). Finally, continuance intention (3 items) was adapted from Bhattacherjee (2001) and Yuan et al. (2016). All items were rated on a seven-point

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Likert scale, ranging from "strongly disagree" to "strongly agree." The second part of the questionnaire gathered demographic information, including respondents' gender, age, education level, and their experience with AI-enabled mobile banking (AIMB). To ensure clarity, readability, and reliability, multiple revisions were made during the design process (see Appendix).

Sampling and Data Collection

Data for this study were collected through a questionnaire survey to empirically test the research model. The survey targeted users with experience in AI-enabled mobile banking applications, particularly those who had directly interacted with AI features in banking or financial services. Focusing on experienced users allowed for an in-depth understanding of their evaluations of AI characteristics such as intelligence and anthropomorphism. Since the original measurement scales were developed in English, the survey underwent a translation and back-translation process to produce a Chinese version. To ensure face and content validity, three experts in mobile banking and AI reviewed the survey for clarity, effectiveness, and interpretability. Based on their feedback, the survey was revised multiple times before being pilot-tested with 50 AI-enabled mobile banking users. Final adjustments were made to improve readability and coherence. Following Lee and Chen (2022), the length of the questionnaire was controlled to maintain quality without losing detail.Before distribution, the minimum sample size for statistical analysis was calculated using GPower software (Faul et al., 2009) to ensure sufficient power for Partial Least Squares Structural Equation Modeling (PLS-SEM). Following Lee et al. (2023), the parameters for GPower included a moderate effect size ($f^2 = 0.15$), a significance level of 0.05, a power level of 0.95, and a maximum of 4 predictors for continuance intention, resulting in a minimum sample size of 129. The final sample exceeded this requirement.

The survey was administered through the professional online platform www.sojump.com, allowing for random sampling instead of convenience sampling (Lee and Wang, 2022). Following Lee et al. (2023), the questionnaire began with an introduction to AI-enabled mobile banking and a screening question to confirm that respondents had used such applications for banking or financial tasks. Only those who answered "yes" proceeded to the full survey. A total of 450 questionnaires were distributed across China, yielding 434 responses. After excluding 39 incomplete responses, 395 valid questionnaires remained for analysis, with a response rate of 87.78%. Demographic information of the sample is presented in Table 1. To ensure representativeness, non-response bias was tested using Armstrong and Overton’s (1977) extrapolation method, which assumes that late respondents are more likely to resemble non-respondents. A comparison between the earliest and latest 25% of responses revealed no significant differences, indicating no non-response bias and confirming the sample’s representativeness.

Table 1. Demographic profile

Variables	Characteristics	Frequency	%
AIMB usage experience	Yes	395	100
	Never	0	0
Gender	Male	188	47.6
	Female	164	41.5
	Prefer not to say	43	10.9
Age	18-24	140	35.4
	25-34	96	24.3
	35-44	68	17.2
	45-54	67	17.0
	Above 55	24	6.1
Education	Below Diploma	40	10.1
	Diploma	72	18.2
	Bachelor	175	44.3
	Above Bachlor	108	27.3
Usage-Duration uses	Less than 6 months	175	44.3
	6 months to 1 year	92	23.3
	1–2 years	65	16.5
	More than 2 years	63	15.9

Note(s):N = 395;
Source(s): Created by authors

Common Method Bias

Following MacKenzie and Podsakoff's (2012) recommendations, several preventive measures were implemented at the outset of this study to reduce the impact of common method bias (CMB). These included optimizing questionnaire structure, randomizing item order, adjusting scale types and anchor labels, and informing respondents that while some items may appear similar, each question addresses unique aspects, encouraging careful responses. In addition, three post hoc statistical tests were conducted to further assess the presence of CMB.

First, a Harman's single-factor test was performed, revealing that the first factor explained only 33.99% of the total variance, which is below the 50% threshold, indicating that CMB is unlikely to be a significant issue in this study. Second, following the guidance of Lee et al. (2022), a full collinearity assessment was conducted using variance inflation factor (VIF) values to detect collinearity. Results showed that all VIF values were below the recommended threshold of 3.3 (see Table 2), providing further evidence that CMB is not a significant concern in this study. Lastly, the marker variable technique (Simmering et al., 2015) was applied, using respondents' education level as the marker variable (following Cao et al., 2021), as it theoretically has no relationship with AI characteristics (intelligence and anthropomorphism) or TCT constructs. The analysis indicated no statistically significant correlations between education level and any variables in the model.In summary, CMB

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

does not significantly impact the results of this study.

Table 2. The collinearity test for CMB.

	ATT	CI	CONF	PA	PEOU	PI	PU	SAT	TA	TA x SAT
ATT		1.602								
CI										
CONF							1.198	1.212		
PA			1.065		1.065		1.131			
PEOU	1.337						1.225			
PI			1.065		1.065		1.259			
PU	1.312	1.378						1.212		
SAT	1.386	1.511								
TA		1.096								
TA x SAT		1.019								

Note(s):N = 395;ATT: Attitude; CI: Continuance Intention; CONF: Confirmation; PA: Perceived Anthropomorphism; PEOU: Perceived Ease of Use; PI: Perceived Intelligence; PU: Perceived Usefulness; SAT: Satisfaction; TA: Technology Anxiety.
Source(s): Created by authors

RESULTS

This study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) combined with Confirmatory Composite Analysis (CCA) to evaluate the proposed model, following the guidelines of Hair et al. (2020) and Cuesta-Valino et al. (2022). PLS-SEM was selected due to its robustness against distribution assumptions, making it suitable for handling model complexity, small sample sizes, and non-normal data, while addressing multicollinearity issues effectively (Hair et al., 2013; Lee et al., 2018). Unlike covariance-based SEM (CB-SEM), PLS was preferred for this study for two main reasons: first, the model's complexity, involving ten hypotheses and various mediation paths, is better suited for PLS than CB-SEM (Hair et al., 2017; Ringle et al., 2012); second, the exploratory nature of this study, given the unclear effects of AI characteristics (e.g., intelligence and anthropomorphism) on ECM in the literature, makes PLS particularly appropriate for exploratory research (Hair et al., 2017; Ringle et al., 2012).For data analysis, SmartPLS 4.0 software (Ringle et al., 2015; Hair et al., 2020) was used. The PLS-SEM analysis followed a two-step procedure: first, the measurement model was assessed for reliability and validity of the latent constructs, and then, in the structural model phase, the data collected from the questionnaire were used to estimate the relationships within the latent variable model (Hair et al., 2020).

Measurement Model Testing

To ensure the consistency of the data, we first assessed the model's reliability and validity. Reliability was evaluated using Cronbach's α coefficients, while validity and internal consistency were

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

tested through Confirmatory Factor Analysis (CFA). As shown in Table 3, Cronbach's α values ranged from 0.862 to 0.935, surpassing the acceptable threshold of 0.7 (Christmann and Van Aelst, 2006), indicating strong reliability. Convergent validity was examined based on the criteria outlined by Hair et al. (2020), where outer loadings exceeded 0.7, the Average Variance Extracted (AVE) was greater than 0.5, and Composite Reliability (CR) values surpassed 0.7. All item loadings met the 0.7 threshold, and both AVE and CR values for all constructs exceeded the recommended standards, confirming convergent validity.

Table 3. Measurement model results.

Construct	Items	M	S.D.	λ	α	CR	AVE
Attitude	ATT1	4.767	1.537	0.999	0.887	0.930	0.816
	ATT2	4.871	1.523	0.977			
	ATT3	4.843	1.574	1.022			
Continuance Intention	CI1	3.914	1.454	1.015	0.862	0.916	0.784
	CI2	3.919	1.412	0.986			
	CI3	3.856	1.478	0.999			
Confirmation	CONF1	5.182	1.543	1.030	0.917	0.941	0.800
	CONF	5.309	1.520	0.979			
	CONF	5.284	1.513	0.969			
	CONF	5.210	1.546	1.022			
Perceived Anthropomorphism	PA1	4.939	1.440	0.990	0.935	0.948	0.754
	PA2	4.997	1.473	1.000			
	PA3	5.020	1.407	0.941			
	PA4	4.962	1.479	1.011			
	PA5	5.010	1.481	1.004			
	PA6	4.929	1.516	1.059			
Perceived Ease of Use	PEOU1	5.089	1.407	0.988	0.922	0.941	0.763
	PEOU	5.109	1.453	1.027			
	PEOU	5.119	1.415	0.986			
	PEOU	5.167	1.466	1.022			
	PEOU5	5.071	1.396	0.977			
Perceived Intelligence	PI1	4.947	1.460	0.992	0.935	0.949	0.755
	PI2	4.970	1.423	0.966			
	PI3	4.967	1.505	1.033			
	PI4	4.995	1.519	1.044			
	PI5	4.962	1.452	0.990			
	PI6	4.904	1.436	0.983			
Perceived Usefulness	PU1	4.729	1.398	0.964	0.903	0.932	0.775
	PU2	4.699	1.466	1.015			
	PU3	4.709	1.472	1.004			
	PU4	4.777	1.453	1.019			
Satisfaction	SAT1	5.000	1.533	1.014	0.916	0.941	0.799
	SAT2	5.051	1.510	1.000			
	SAT3	5.068	1.519	0.988			
	SAT4	5.109	1.513	0.999			

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Technology Anxiety	TA1	4.759	1.457	1.017	0.876	0.923	0.801
	TA2	4.752	1.428	0.994			
	TA3	4.803	1.450	0.989			

Note(s):N = 395; M: Mean; S.D.: Standard deviation; λ: Outer loadings; α: Cronbach's alpha; CR: Composite reliability; AVE: Average variance extracted.The average variance extracted (AVE) of each construct should exceed the threshold value of 0.5 (Hair et al., 2013). The acceptable level of factor loading, composite reliability,and Cronbach's α is 0.7 (Hair et al., 2013).
Source(s): Created by authors

Next, we evaluated discriminant validity using the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. As shown in Table 4, the Fornell-Larcker criterion results indicate that the diagonal values (bolded) represent the highest correlation for each construct within its column. Furthermore, the HTMT ratio, a reliable method for assessing discriminant validity in structural equation models, was employed. The results in Table 5 show that all HTMT values were below the 0.85 threshold, confirming the model's strong discriminant validity.

Table 4. Discriminant validity: Fornell-Larcker criterion.

	ATT	CI	CONF	PA	PEOU	PI	PU	SAT	TA
ATT	0.903								
CI	0.501	0.885							
CONF	0.398	0.423	0.895						
PA	0.387	0.406	0.233	0.868					
PEOU	0.445	0.442	0.285	0.274	0.873				
PI	0.372	0.430	0.348	0.247	0.355	0.869			
PU	0.470	0.513	0.418	0.395	0.396	0.349	0.880		
SAT	0.538	0.500	0.431	0.352	0.449	0.401	0.432	0.894	
TA	-0.249	-0.224	-0.167	-0.173	-0.173	-0.172	-0.216	-0.241	0.895

Note(s):N = 395;ATT: Attitude; CI: Continuance Intention; CONF: Confirmation; PA: Perceived Anthropomorphism; PEOU: Perceived Ease of Use; PI: Perceived Intelligence; PU: Perceived Usefulness; SAT: Satisfaction; TA: Technology Anxiety.
Source(s): Created by authors

Table 5. HTMT analysis results.

	ATT	CI	CONF	PA	PEOU	PI	PU	SAT	TA	TAxSAT
ATT										
CI	0.572									
CONF	0.441	0.477								
PA	0.422	0.451	0.251							
PEOU	0.490	0.496	0.310	0.294						
PI	0.407	0.478	0.374	0.263	0.381					
PU	0.522	0.582	0.459	0.429	0.434	0.378				

SAT	0.596	0.562	0.470	0.380	0.488	0.432	0.474		
TA	0.284	0.257	0.188	0.186	0.193	0.189	0.242	0.269	
TAxSAT	0.116	0.063	0.132	0.042	0.062	0.071	0.014	0.046	0.026

Note(s):N = 395;ATT: Attitude; CI: Continuance Intention; CONF: Confirmation; PA: Perceived Anthropomorphism; PEOU: Perceived Ease of Use; PI: Perceived Intelligence; PU: Perceived Usefulness; SAT: Satisfaction; TA: Technology Anxiety.
Source(s): Created by authors

Testing the Research Hypotheses

Structural Equation Modeling (SEM) was used to evaluate the hypothesized relationships. To assess the significance of path coefficients, this study employed a bootstrapping method with 10,000 resamples to calculate the p-values of the path coefficients. The R^2 values for all endogenous variables exceeded the recommended threshold of 0.10 (Falk and Miller, 1992), demonstrating the model's robust explanatory power for continuance intention, with an R^2 value of 0.402 for continuance intention itself. The results of hypothesis testing are summarized in Table 6 and illustrated in Figure 2.

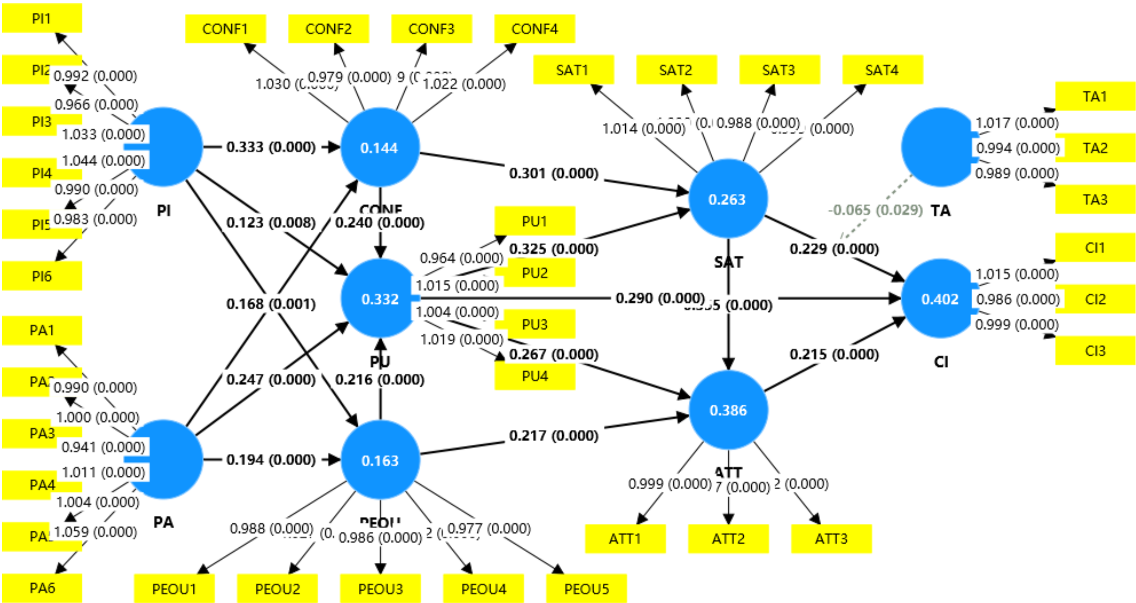
Table 6. Hypothetical relationship test results.

Hypothesis	Path	β	S.D.	T-Value	P-Value	f^2	Supported [Yes/No]
H1	CONF→SAT	0.301***	0.048	2.942	0.000	0.103	Yes
H2	CONF→PU	0.240***	0.042	2.745	0.000	0.083	Yes
H3	PEOU→ATT	0.217***	0.049	2.072	0.000	0.046	Yes
H4	PEOU→PU	0.216***	0.049	2.051	0.000	0.055	Yes
H5	PU→SAT	0.325***	0.052	2.874	0.000	0.104	Yes
H6	PU→ATT	0.267***	0.048	2.703	0.000	0.074	Yes
H7	PU→CI	0.290***	0.048	2.794	0.000	0.101	Yes
H8	SAT→CI	0.229***	0.047	2.329	0.000	0.065	Yes
H9	SAT→ATT	0.355***	0.050	3.316	0.000	0.140	Yes
H10	ATT→CI	0.215***	0.047	2.229	0.000	0.057	Yes
H11a	PI→CONF	0.333***	0.053	2.786	0.000	0.105	Yes
H11b	PI→PU	0.123***	0.046	1.295	0.008	0.018	Yes
H11c	PI→PEOU	0.300***	0.048	2.866	0.000	0.105	Yes
H12a	PA→CONF	0.168**	0.051	1.567	0.001	0.027	Yes
H12b	PA→PU	0.247***	0.042	2.568	0.000	0.081	Yes
H12c	PA→PEOU	0.194***	0.049	1.915	0.000	0.044	Yes
H13	TA×SAT→CI	-0.065*	0.030	1.035	0.029	0.014	Yes

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

Note(s):N = 395; *p < 0.05. **p < 0.01. ***p < 0.001; S.D.: Standard deviation;ATT: Attitude; CI: Continuance Intention; CONF: Confirmation; PA: Perceived Anthropomorphism; PEOU: Perceived Ease of Use; PI: Perceived Intelligence; PU: Perceived Usefulness; SAT: Satisfaction; TA: Technology Anxiety.
Source(s): Created by authors

Figure 2 Structural model results.



The results reveal that perceived intelligence (PI) significantly influences confirmation, perceived usefulness (PU), and perceived ease of use (PEOU), with path coefficients of β = 0.333 (p < 0.001), β = 0.123 (p < 0.01), and β = 0.300 (p < 0.001), respectively, confirming hypotheses H11a, H11b, and H11c. Similarly, perceived anthropomorphism (PA) has a significant positive effect on confirmation, perceived usefulness, and perceived ease of use, with path coefficients of β = 0.168 (p < 0.01), β = 0.247 (p < 0.001), and β = 0.194 (p < 0.001), supporting hypotheses H12a, H12b, and H12c. Confirmation (CONF) positively influences satisfaction (SAT) and perceived usefulness, with path coefficients of β = 0.301 (p < 0.001) and β = 0.240 (p < 0.001), validating hypotheses H1 and H2. Perceived usefulness also significantly impacts satisfaction and continuance intention (CI), with path coefficients of β = 0.325 (p < 0.001) and β = 0.290 (p < 0.001), confirming hypotheses H5 and H7. Satisfaction demonstrates a positive effect on continuance intention (β = 0.229, p < 0.001), supporting hypothesis H8, while attitude (ATT) also positively affects continuance intention (β = 0.215, p < 0.001), confirming hypothesis H10. All other hypotheses, not detailed here, were supported with significant positive effects. Importantly, technology anxiety (TA) negatively moderates the relationship between satisfaction and continuance intention (β = -0.065, p < 0.05), supporting

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

hypothesis H13 (see Figure 3).

Figure 3 Moderation effect of technology anxiety on the relationship between satisfaction and continuance usage intention.

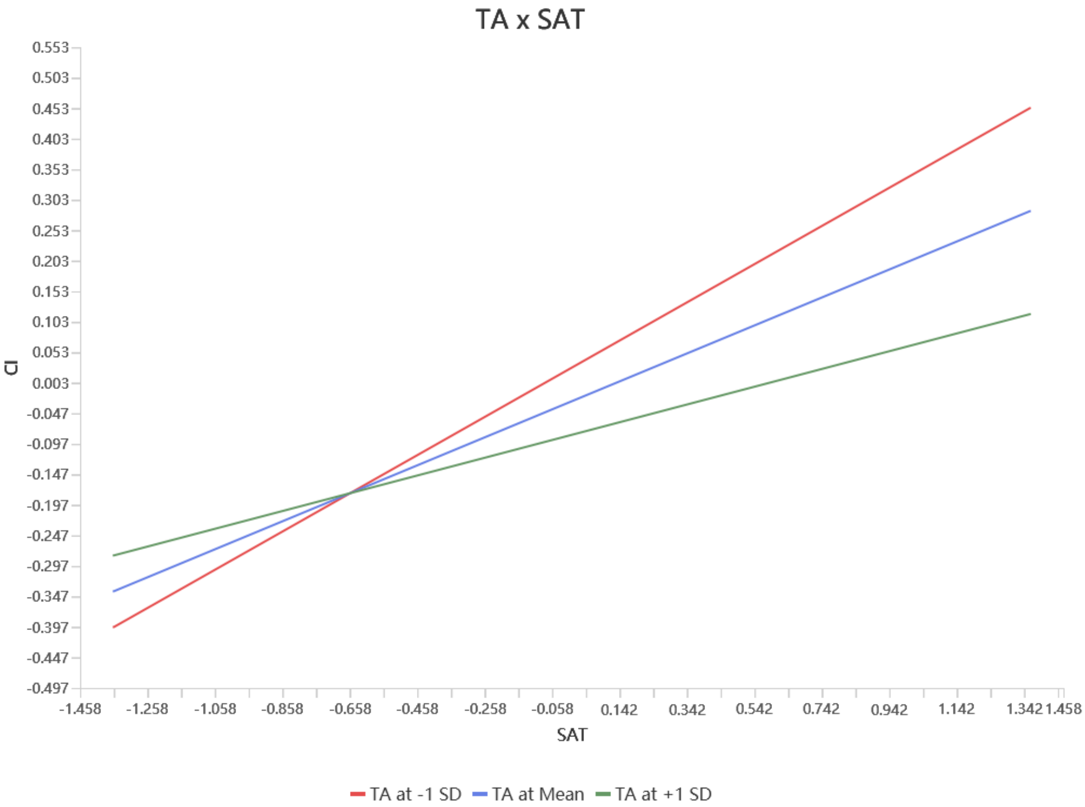


Table 7 summarizes the results of the indirect effect analysis. Following Zhao et al. (2010), mediation effects were tested to examine how independent variables influence dependent variables via relevant mediators. This study investigates the mediating roles of AI characteristics, specifically perceived intelligence and perceived anthropomorphism, within the Technology Continuance Theory (TCT) framework. The analysis reveals that both perceived intelligence and perceived anthropomorphism exert significant indirect effects on satisfaction, perceived usefulness, attitude, and continuance intention through various mediators.Perceived intelligence, for instance, indirectly influences satisfaction and perceived usefulness via confirmation, with indirect effects of $\beta = 0.100$ ($p < 0.001$) and $\beta = 0.080$ ($p < 0.001$), indicating significant complementary mediation. Similarly, perceived anthropomorphism has indirect effects on satisfaction and perceived usefulness through confirmation, with indirect effects of $\beta = 0.051$ ($p < 0.01$) and $\beta = 0.040$ ($p < 0.01$).Additionally, both perceived intelligence and perceived anthropomorphism influence perceived usefulness and attitude via perceived ease of use. The PI-PEOU-PU path shows an indirect effect of $\beta = 0.065$ ($p < 0.01$), and the PA-PEOU-ATT path has an indirect effect of $\beta = 0.042$ ($p < 0.01$). When perceived usefulness mediates the relationship, both AI characteristics significantly affect continuance intention, especially

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

in the PA-PU-CI path, with an indirect effect of $\beta = 0.072$ ($p < 0.001$), indicating a distinct indirect-only mediation effect.Overall, these findings highlight that perceived intelligence and perceived anthropomorphism influence satisfaction, attitude, and continuance intention through multiple layers of indirect effects, reinforcing the mediating role of AI characteristics within the TCT framework.

Table 7. Indirect effects.

No	Mediation regression coefficient Path	Indirect effects	S.D.	T-Value	P-Value	95% CIs	
						LL	UL
1	PI→CONF→SAT	0.100***	0.024	4.118	0.000	0.058	0.153
2	PI→CONF→PU	0.080***	0.019	4.105	0.000	0.046	0.123
3	PA→CONF→SAT	0.051**	0.019	2.699	0.007	0.018	0.093
4	PA→CONF→PU	0.040**	0.015	2.756	0.006	0.016	0.073
5	PI→PEOU→PU	0.065**	0.019	3.470	0.001	0.033	0.106
6	PI→PEOU→ATT	0.065**	0.020	3.322	0.001	0.032	0.108
7	PA→PEOU→PU	0.042**	0.015	2.859	0.004	0.018	0.076
8	PA→PEOU→ATT	0.042**	0.015	2.792	0.005	0.018	0.077
9	PI→PU→SAT	0.040*	0.017	2.342	0.019	0.011	0.078
10	PI→PU→ATT	0.033*	0.014	2.426	0.015	0.010	0.063
11	PI→PU→CI	0.036*	0.015	2.364	0.018	0.010	0.070
12	PA→PU→SAT	0.080***	0.019	4.218	0.000	0.046	0.121
13	PA→PU→ATT	0.066***	0.017	3.774	0.000	0.036	0.105
14	PA→PU→CI	0.072***	0.017	4.164	0.000	0.042	0.110

Note(s):N = 395; *p < 0.05. **p < 0.01. ***p < 0.001; S.D.: Standard deviation;ATT: Attitude; CI: Continuance Intention; CONF: Confirmation; PA: Perceived Anthropomorphism; PEOU: Perceived Ease of Use; PI: Perceived Intelligence; PU: Perceived Usefulness; SAT: Satisfaction; TA: Technology Anxiety;CIs: Confidence intervals; LL: Low limit; UL: Upper limit.
Source(s): Created by authors

DISCUSSION AND CONCLUSION

Key findings and theoretical contributions

In using mobile banking applications, it is essential to consider the influence of artificial intelligence (AI) on user adoption behavior (Lee and Chen, 2022). The primary goal of this study was to integrate AI characteristics with the Technology Continuance Theory (TCT) to examine users' continuance intention toward AI-enabled mobile banking applications (AIMB). Empirical analysis provided support for all proposed hypotheses, including the extended TCT hypotheses (H1-H10) in the context of AI-enabled mobile banking. These findings align with prior research (Foroughi et al., 2019; Ahayer and Bao, 2019; Rahi et al., 2021; Aprilia and Amalia, 2023).

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

First, although previous studies have examined the characteristics of AI and their influence on continuance intention, suggesting that AI characteristics impact perceived ease of use and confirmation, they have yet to fully explore the comprehensive mechanism by which AI features affect continuance intention toward AIMB (Lee et al., 2023). This study is the first to combine AI characteristics with TCT to investigate AIMB continuance intention. The findings demonstrate that intelligence and anthropomorphism significantly enhance users' confirmation of AI-enabled mobile banking applications (H11a and H12a), improving the user experience and meeting their expectations, which reinforces users' belief in the applications' practical usefulness. The intelligence characteristic enables rapid identification and response to user needs, fulfilling their expectations for transaction completion and personalized services, thereby enhancing trust and consistent user experience. The anthropomorphic characteristic, by imbuing the application with human-like communication abilities, creates a natural and comfortable interaction that mimics interpersonal communication, deepening users' emotional connection and engagement. Additionally, both intelligence and anthropomorphism positively affect perceived usefulness (H11b and H12b). Users generally perceive that AI technology effectively meets their needs for transactions and banking services, providing a smooth and convincing experience. This perception positions AIMB as a trusted assistant capable of understanding and responding to users' needs, thereby enhancing their satisfaction and positive attitude, ultimately leading to a stronger intention to continue using the application. Intelligence and anthropomorphism also significantly influence perceived ease of use (H11c and H12c), making users feel that the application is easy to operate and reduces psychological burden. With intelligent and anthropomorphic features, users experience smoother interactions that feel more like interpersonal communication, reducing learning costs and enhancing perceived ease of use. Overall, intelligence and anthropomorphism shape positive user experiences and preferences for the application through confirmation, perceived usefulness, and perceived ease of use, consistent with prior AI adoption literature (e.g., Moussawi et al., 2020; Lee et al., 2023).

Second, mediation analysis reveals that intelligence and anthropomorphism influence various aspects of user experience through confirmation, perceived ease of use, and perceived usefulness, which shape users' behavioral intentions. Specifically, intelligence reinforces users' confirmation by meeting their expectations in transactions and personalized services, thereby enhancing satisfaction and perceived usefulness. Anthropomorphism, by creating an interaction style closer to interpersonal communication, makes users feel comfortable during use, strengthening their emotional connection and trust. This emotionally connected experience effectively reduces the distance and unfamiliarity users may feel when interacting with an AI system, enhancing their attitude and overall satisfaction. Perceived ease of use plays a bridging role in this process, reducing users' learning costs and psychological burden, thus providing a smoother and more intuitive operational experience. This sequential influence strengthens users' positive evaluations and continuance intention. Confirmation, perceived ease of use, and perceived usefulness form a multi-level pathway by which intelligence and anthropomorphism translate into positive experiences and behaviors, simultaneously satisfying users' rational and emotional needs. This dual satisfaction enables users to perceive both the practical value and interpersonal comfort of the application, fostering loyalty toward the application. Overall, intelligence and anthropomorphism effectively meet user needs through multiple pathways, providing a robust theoretical foundation for optimizing user experience and strategic design of AI-enabled mobile banking applications, thus enhancing their competitiveness in the market.

Finally, although AI literature emphasizes satisfaction as a key factor influencing behavioral intention and continued use of technological systems (Maduku and Thusi, 2023), limited research currently explores how user satisfaction enhances continuance intention toward AIMB. This study contributes to the existing body of knowledge by explaining the relationship between AI characteristics, satisfaction with AIMB services, and continuance intention. Additionally, prior studies have highlighted technology anxiety as a psychological barrier affecting users' interactions with AI-driven tools (Debasa et al., 2023; Maduku et al., 2023; Rahmani et al., 2023). This study is the first to demonstrate the negative moderating role of technology anxiety in the relationship between satisfaction and continuance intention, particularly noting that users with higher levels of technology anxiety exhibit weaker correlations between satisfaction and continuance intention. By extending and validating the application of TCT within the proposed model, this study enriches the AIMB literature and reveals the role of intelligence and anthropomorphism in fostering continuance intention toward AIMB. Although the TCT model has been recognized for exploring behaviors related to mobile banking continuance, this study is the first to apply TCT to clarify how the AI characteristics of intelligence and anthropomorphism influence users' continuance intention toward AIMB.

Practical and managerial implications

Mobile banking plays a crucial role in advancing the banking sector, with AI technology further enhancing user experience and market competitiveness. However, increasing user continuance remains a pressing issue (Merhi et al., 2019). Based on this study's empirical findings, particularly the moderating role of technology anxiety, several practical recommendations for implementing AI in mobile banking applications are proposed.

First, this study found that intelligence and anthropomorphism significantly enhance user confirmation, perceived usefulness, and perceived ease of use. This suggests that development teams can embed appropriate AI algorithms to better meet users' personalized financial needs. For example, AI can offer customized financial advice based on users' spending patterns, savings habits, and investment preferences, such as budgeting guidance, investment insights, or savings plans. By providing tailored recommendations aligned with user risk tolerance and personal data, such precise services not only improve the relevance and convenience of the user experience but also increase satisfaction and trust, fostering continuance intention. For instance, conservative users might receive low-risk investment options, while high-return seekers could be offered suggestions aligning with

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

their goals, addressing individual financial needs.

Second, given the negative moderating effect of technology anxiety on the relationship between satisfaction and continuance intention, this study recommends enhancing the intelligence and reliability of AI in system design to reduce operational errors and potential system failures. Especially in scenarios requiring high accuracy for financial transactions, AI systems need to effectively detect anomalies or potential errors and provide real-time alerts to prevent user mistakes. For example, systems could remind users when an incorrect account number is entered or when an unusually large transfer is initiated. Such intelligent safeguards not only ease the concerns of users with technology anxiety but also enhance system security and stability, increasing users' trust and security perception for a more positive experience.

As users increasingly demand AI intelligence, it becomes essential to further enhance AI's deep learning capabilities and response speed to meet evolving user needs. Developers could leverage Natural Language Processing (NLP) technology, enabling users to receive personalized, real-time advice through simple verbal or text queries, such as "What is the safest investment option right now?" or "How can I increase my savings?" For users with high technology anxiety, AI's fast responses and intuitive interaction can significantly reduce the complexity and rejection associated with using the technology, thereby enhancing trust and reliance on the application.

Additionally, anthropomorphism plays a significant role in improving user experience and alleviating technology anxiety. Research indicates that anthropomorphic characteristics enhance users' emotional experience by creating an interaction that resembles interpersonal communication, allowing users to feel more natural and comfortable during use. Developers can optimize anthropomorphic elements in the interaction interface, such as virtual avatars, language style, and personalized greetings, to enhance the interactive experience. For instance, an AI assistant could greet users by name and interact with supportive language, such as "Hello, [User Name], how can I assist you in finding more options?" This personalized interaction style, particularly beneficial for users with high technology anxiety, significantly reduces their feelings of alienation, allowing them to perceive AI not just as a cold tool but as a "companion" that understands their needs, further enhancing satisfaction and continuance intention.

Finally, banks can encourage users, especially those with higher technology anxiety, to prioritize AI services for routine inquiries in their daily operations. For instance, promoting AI-powered automated FAQs encourages users to rely on AI assistants for tasks such as balance inquiries, transaction history checks, or loan information retrieval. Banks could offer a "tutorial mode" to demonstrate AI interaction processes, explaining how the system works and its security features in detail. This guidance helps users gradually adapt to and trust AI, easing technology anxiety and providing a more comfortable experience when they encounter questions or technical issues. By implementing these practices, banks can effectively optimize the AI-driven mobile banking user experience, reduce user anxiety, enhance continuance intention, maximize the value of AI technology,

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

and ultimately increase user satisfaction and loyalty.

Limitations and avenue for further research

This study contributes significantly to both theory and practice but also has limitations that suggest avenues for future research. First, the survey sample is restricted to China, which may limit the generalizability of the findings to other countries and regions. To enhance the external validity of the results, future research should broaden the sample to include participants from diverse geographical areas and cultural contexts. Second, although the sample size meets the minimum requirement established by G*Power and passed non-response bias testing, its relatively small size may introduce some bias. Future studies should consider increasing the sample size to improve the robustness and representativeness of the findings. Furthermore, this research utilized a cross-sectional survey design, which, while effective in capturing current user behaviors, does not allow for the establishment of causal relationships. Longitudinal studies would be valuable in examining how users' continuance intention toward AI-enabled mobile banking evolves over time.

Future research should explore the deeper effects of personality traits, service quality, and technological advancements on continuance intention toward AI-enabled mobile banking (AIMB). Personality traits, such as those in the Big Five, significantly influence users' attitudes and technology adoption behaviors, suggesting that aligning AI features with personality types could optimize services, for instance, by offering advanced functions for open users or emphasizing security for conscientious users. Examining the combined influence of personality traits and AI characteristics, including intelligence and anthropomorphism, could clarify how personalized services impact user acceptance and help development teams address diverse needs. Furthermore, AI agent service quality (AISAQUAL) is essential for enhancing user experience and promoting continuance. As AI integrates further into mobile banking, service quality should include responsiveness, warmth, and interaction quality alongside technical reliability. This approach, combined with TCT, could reveal service quality's role in driving AIMB continuance. With rapid advancements in AI and natural language processing, research should also examine how functional enhancements, such as conversational AI and intelligent recommendations, impact user experience. Emotionally responsive AI assistants that offer support during user uncertainty could improve flow, reduce technology anxiety, and enhance satisfaction. Studying these impacts could deepen insights into AI's role in mobile banking, guiding banks and fintech companies in creating more personalized and humanized services.

AUTHOR INTRODUCTION

Shuoteng HUANG, PhD Candidate at aSSIST University(Seoul School of Integrated Sciences & Technologies),Research interests include Consumer behavio, Financial decision-making and literacy education,Law education,Technology adoption.

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Fei HUANG, Assistant professor at aSSIST University(Seoul School of Integrated Sciences & Technologies),Research interests include corporate strategy, internationalization, sustainable development management, and brand management

REFERENCE

[1] Aggelidis, V. P., & Chatzoglou, P. D. (2009). Using a modified technology acceptance model in hospitals. International Journal of Medical Informatics, 78, 115–126. https://doi.org/10.1016/j.ijmedinf.2008.06.006

[2] Ahayer, K., & Bao, Y. (2019). The continuance usage intention of Alipay: Integrating context-awareness and technology continuance theory (TCT). *The Bottom Line, 32*(3), 211-229.

[3] Albort-Morant, G., Sanchís-Pedregosa, C., & Paredes Paredes, J. R. (2021). Online banking adoption in Spanish cities and towns. Finding differences through TAM application. Economic Research-Ekonomska Istrazivanja, 9, 1–19.

[4] Albuhisi, A.M., & Abdallah, A.B. (2018). The impact of soft TQM on financial performance. *International Journal of Quality and Reliability Management, 35*(7), 1360-1379. https://doi.org/10.1108/ijqrm-03-2017-0036

[5] Alimamy, S., & Gnoth, J. (2022). I want it my way! The effect of perceptions of personalization through augmented reality and online shopping on customer intentions to co-create value. *Computers in Human Behavior, 128*, 107105. https://doi.org/10.1016/j.chb.2021.107105

[6] Alraimi, K.M., Zo, H., & Ciganek, A.P. (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers and Education, 80*, 28-38.

[7] Armstrong, J.S., & Overton, T.S. (1977). Estimating nonresponse bias in mail surveys. *Journal of Marketing Research, 14*(3), 396–402.

[8] Aprilia, C., & Amalia, R. (2023). Perceived security and technology continuance theory: An analysis of mobile wallet users' continuance intention. *Global Business Review*. https://doi.org/10.1177/09721509221145831

[9] Balakrishnan, J., & Dwivedi, Y.K. (2021). Conversational commerce: Entering the next stage of AI-powered digital assistants. *Annals of Operations Research*, 1-35. https://doi.org/10.1007/s10479-021-04049-5

[10] Banerjee, S., & Sreejesh, S. (2022). Examining the role of customers' intrinsic motivation on continued usage of mobile banking: A relational approach. *International Journal of Bank Marketing, 40*(1), 87–109.

[11] Bhatnagr, P., Rajesh, A., & Misra, R. (2024). Continuous intention usage of artificial intelligence-enabled digital banks: A review of expectation confirmation model. *Journal of Enterprise Information Management*.

[12] Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly, 25*(3), 351–370.

[13] Bhattacherjee, A., & Barfar, A. (2011). Information technology continuance research: Current state and future directions. *Asia Pacific Journal of Information Systems*, 21, 1–18.

[14] Campanelli, A.S., Camilo, R.D., & Parreiras, F.S. (2018). The impact of tailoring criteria on agile practices adoption: A survey with novice agile practitioners in Brazil. *Journal of Systems and Software, 137*, 366–379.

[15] Cao, G., Duan, Y., Edwards, J.S., & Dwivedi, Y.K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. *Technovation, 106*, 102312.

[16] Cheng, P., Meng, F., Yao, J. and Wang, Y. (2022), "Driving with agents: investigating the influences of anthropomorphism level and physicality of agents on drivers' perceived control, trust, and driving performance", *Frontiers in Psychology, Vol. 13*, 883417, doi: 10.3389/fpsyg.2022.883417.

[17] Cheng, Y. M. (2011). Antecedents and consequences of e-learning acceptance. *Information Systems Journal, 21,* 269–299. https://doi.org/10.1111/j.1365-2575.2010.00356.x

[18] Chitungo, S.K., & Munongo, S. (2013). Extending the technology acceptance model to mobile banking adoption in rural Zimbabwe. *Journal of Business Administration and Education, 3*(1), 51-79.

[19] Creswell, J. W. (2013). Research design: Qualitative, quantitative, and mixed methods approaches. Sage publications.

[20] Cuesta-Valino, P., Gutiérrez-Rodríguez, P., & García-Henche, B. (2022). Word of mouth and digitalization in small retailers: Tradition, authenticity, and change. *Technological Forecasting and Social Change, 175*, 121382.

[21] Davis, F.D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

[22] Davis, F. D., Bagozzi, R., & Warshaw, P. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*,982–1003. https://doi.org/10.1287/mnsc.35.8.982

[23] Debasa, F., Gelashvili, V., Martínez-Navalon, J.G., & Saura, J.R. (2023). Do stress and anxiety influence users' intention to make restaurant reservations through mobile apps? *European Research on Management and Business Economics, 29*(1). https://doi.org/10.1016/j.iedeen.2022.100205

[24] Ding, Z., Saide, S., Siti Astuti, E., Muwardi, D., Najamuddin, N., Jannati, M., & Herzavina, H. (2019). An adoption of acceptance model for the multi-purpose system in university library. Economic Research-Ekonomska Istraživanja, 32, 2393–2403. https://doi.org/10.1080/1331677X.2019.1635898

[25] Doumpos, M., Zopounidis, C., Gounopoulos, D., Platanakis, E., & Zhang, W. (2023). Operational research and artificial intelligence methods in banking. *European Journal of Operational Research, 306*(1), 1-16.

[26] Elhajjar, S., & Ouaida, F. (2019). An analysis of factors affecting mobile banking adoption. *International Journal of Bank Marketing, 38*(2), 352–367.

[27] Farah, M. F., Hasni, M. J. S., & Abbas, A. K. (2018). Mobile-banking adoption: empirical evidence from the banking sector in Pakistan. *International Journal of Bank Marketing, 36*(7), 1386-1413.

[28] Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149–1160.

[29] Foroughi, B., Iranmanesh, M., & Hyun, S.S. (2019). Understanding the determinants of mobile banking continuance usage intention. *Journal of Enterprise Information Management, 32*(6), 1015–1033.

[30] Franque FB, Oliveira T, Tam C, de Oliveira Santini F (2021) A meta-analysis of the quantitative studies in continuance intention to use an information system. Internet Res 31(1):123–158

[31] Fu, X., Zhang, J., & Chan, F.T.S. (2018). Determinants of loyalty to public transit: A model integrating satisfaction-loyalty theory and expectation-confirmation theory. *Transportation Research Part A: Policy and Practice, 113*, 476–490.

[32] Gilani, M.S., Iranmanesh, M., Nikbin, D., & Zailani, S. (2017). EMR continuance usage intention of healthcare professionals. *Informatics for Health and Social Care, 42*(2), 153–165.

[33] Gu, J. C., Fan, L., Suh, Y. H., & Lee, S. C. (2010). Comparing utilitarian and hedonic usefulness to user intention in multipurpose information systems. *Cyberpsychology, Behavior and Social Networking, 13*, 287–297. https://doi.org/10.1089/cyber.2009.0167

[34] Hair, J.F., Howard, M.C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research, 109*, 101–110.

[35] Hair, J.F., Hult, G.T.M., Ringle, C., & Sarstedt, M. (2013). *A primer on partial least squares structural equation modeling (PLS-SEM)*. SAGE Publications, Thousand Oaks, CA.

[36] Hair, J.F., Hollingsworth, C.L., Randolph, A.B., & Chong, A.Y.L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems, 117*(3), 442–458.

[37] Hamari, J., & Koivisto, J. (2015). Why do people use gamification services? *International Journal of Information Management, 35*(4), 419–431.

[38] Handayani, P. W., Hidayanto, A. N., Pinem, A. A., Hapsari, I. C., Sandhyaduhita, P. I., & Budi, I. (2017). Acceptance model of a hospital information system. *International Journal of Medical Informatics*, 99, 11–28. https://doi.org/10.1016/j.ijmedinf.2016.12.004

[39] Hart, C. (2018). Doing a literature review: Releasing the research imagination. Sage.

[40] Hoehle, H., Huff, S., & Goode, S. (2012). The role of continuous trust in information systems continuance. *Journal of Computer Information Systems, 52*(4), 1-9.

[41] Hsu, C.-L., & Lin, J.C.-C. (2018). Examining social networking O2O apps user loyalty. *Journal of Computer Information Systems*, 1–9.

[42] Huang, M.-H., & Rust, R.T. (2020). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50.

[43] Humbani, M., & Wiese, M. (2019). An integrated framework for the adoption and continuance intention to use mobile payment apps. *International Journal of Bank Marketing, 37*(2), 646-664. https://doi.org/10.1108/ijbm-03-2018-0072

[44] Ifinedo, P. (2016). The moderating effects of demographic and individual characteristics on nurses' acceptance of information systems: A Canadian study. *International Journal of Medical Informatics, 87*, 27–35. https://doi.org/10.1016/j.ijmedinf.2015.12.012

[45] Iranmanesh, M., Zailani, S., & Nikbin, D. (2017). RFID continuance usage intention in the healthcare industry. *Quality Management in Health Care, 26*(2), 116–123.

[46] Israel, D. R., & Malik, G. (2018). Explaining customers' continuance intention to use mobile banking apps with an integrative perspective of ECT and Self-determination theory. *Pacific Asia Journal of the Association for Information Systems, 10*(2), 79-112.

[47] Jennings, G. R. (2010). Research processes for evaluating quality experiences: Reflections from the "experiences". The Tourism and Leisure Experience: Consumer and Managerial Perspectives, 44, 81.

[48] Kang, J. W., & Namkung, Y. (2019). The role of personalization on continuance intention in food service mobile apps: A privacy calculus perspective. *International Journal of Contemporary Hospitality Management, 31*(2), 734-752. https://doi.org/10.1108/IJCHM-12-2017-0814

[49] Karahanna, E., Straub, D. W., & Chervany, N. L. (1999). Information technology adoption across time: A cross-sectional comparison of pre-adoption and post-adoption belief. *MIS Quarterly, 23*, 183–213. https://doi.org/10.2307/249751

[50] Kaya, O. (2019). Artificial intelligence in banking: A lever for profitability with limited implementation to date. *EU Monitor*, Deutsche Bank Research

[51] Keeves, J. P. (1997). Models and model building. Educational research, methodology, and measurement: An international handbook, 2, 386-394.

[52] Kelly, S., Kaye, S., & Oviedo-Trespalacios, O. (2022). A multi-industry analysis of the future use of AI chatbots. *Human Behavior and Emerging Technologies, 2022*, 1–14. https://doi.org/10.1155/2022/2552099

[53] Kivunja, C., & Kuyini, A. B. (2017). Understanding and applying research paradigms in educational contexts. International Journal of Higher Education, 6(5), 26-41.

[54] Koksal, M.H. (2016). The intentions of Lebanese consumers to adopt mobile banking. *International Journal of Bank Marketing, 34*(3), 327–346.

[55] Kuhn Thomas, S. (1962). The structure of scientific revolutions. Chicago: University of Chicago.

[56] Lee, J.C., Chen, X. (2022). Exploring users' adoption intentions in the evolution of artificial intelligence mobile banking applications: The intelligent and anthropomorphic perspectives. *International Journal of Bank Marketing, 40*(4), 631–658.

[57] Lee, J.C., Hsu, W.C., & Chen, C.Y. (2018). Impact of absorptive capability on software process improvement and firm performance. *Information Technology and Management, 19*(1), 21–35.

[58] Lee, J.C., Tang, Y., & Jiang, S. (2023). Understanding continuance intention of artificial intelligence (AI)-enabled mobile banking applications: An extension of AI characteristics to an expectation confirmation model. *Humanities and Social Sciences Communications, 10*(1), 1–12.

[59] Lee, J.C., Wang, J. (2022). From offline to online: Understanding users' switching intentions from traditional wealth management services to mobile wealth management applications. *International Journal of Bank Marketing*. https://doi.org/10.1108/IJBM-08-2022-0345

[60] Lee, N., & Lings, I. (2008). Doing business research: a guide to theory and practice. Sage.

[61] Li, J., & Huang, J.-S. (2020). Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. *Technology in Society, 63*. https://doi.org/10.1016/j.techsoc.2020.101410

[62] Liao, C., Palvia, P., & Chen, J.-L. (2009). Information technology adoption behavior life cycle: toward a technology continuance theory (TCT). *International Journal of Information Management, 29*(4), 309-320.

[63] Liébana-Cabanillas, F., Ramos de Luna, I., & Montoro-Ríos, F. (2017). Intention to use new mobile payment systems: A comparative analysis of SMS and NFC payments. *Economic Research-Ekonomska Istraživanja, 30*, 892–910. https://doi.org/10.1080/1331677X.2017.1305784

[64] Lim, S. H., Kim, D. J., Hur, Y., & Park, K. (2019). An empirical study of the impacts of perceived security and knowledge on continuous intention to use mobile fintech payment services. *International Journal of Human–Computer Interaction, 35*(10), 886-898.

[65] Linck, K., Pousttchi, K., & Wiedemann, D. G. (2006). Security issues in mobile payment from the customer viewpoint.

[66] Lincoln, Y. G., & Guba, E. G. EG (1985). Naturalistic inquiry.

[67] Lin, H. C., & Chang, C. M. (2018). What motivates health information exchange in social media? The roles of the social cognitive theory and perceived interactivity. *Information & Management,* 55, 771–780.

[68] Lin, H. C., Han, X., Tu, L., Ho, W. H., Xu, Y., Hsieh, T. C., Zhu, L., & Zhang, L. (2020). Task-technology fit analysis of social media use for marketing in the tourism and hospitality industry: A systematic literature review. *International Journal of Contemporary Hospitality Management, 32*, 2677–2715. https://doi.org/10.1108/IJCHM-12-2019-1031

[69] Lin, R.R., Lee, J.C. (2023). The supports provided by artificial intelligence to continuous usage intention of mobile banking: Evidence from China. *Aslib Journal of Information Management*. https://doi.org/10.1108/AJIM-07-2022-0337

[70] Lin, R.R., Zheng, Y., & Lee, J.C. (2023). Artificial intelligence-based pre-implementation interventions in users' continuance intention to use mobile banking. *International Journal of Mobile Communications, 21*(4), 518–540.

[71] Lin, W.-S. (2012). Perceived fit and satisfaction on web learning performance: IS continuance intention and task-technology fit perspectives. *International Journal of Human-Computer Studies, 70*(7), 498-507.

[72] MacKenzie, S.B., & Podsakoff, P.M. (2012). Common method bias in marketing: Causes, mechanisms, and procedural remedies. *Journal of Retailing, 88*(4), 542–555.

[73] Maduku, D. K., Mpinganjira, M., Rana, N. P., Thusi, P., Ledikwe, A., & Mkhize, N. H.-b. (2023). Assessing customer passion, commitment, and word-of-mouth intentions in digital assistant usage: the moderating role of technology anxiety. *Journal of Retailing and Consumer Services, 71*. https://doi.org/10.1016/j.jretconser.2022.103208

[74] Malhotra, G., & Ramalingam, M. (2023). Perceived anthropomorphism and purchase intention using artificial intelligence technology: examining the moderated effect of trust. *Journal of Enterprise Information Management*. https://doi.org/10.1108/jeim-09-2022-0316

[75] Manser Payne, E., Peltier, J.W., & Barger, V.A. (2018). Mobile banking and AI-enabled mobile banking: The differential effects of technological and non-technological factors on digital natives' perceptions and behavior. *Journal of Research in Interactive Marketing, 12*(3), 328–346.

[76] Merhi, M., Hone, K., & Tarhini, A. (2019). A cross-cultural study of the intention to use mobile banking between Lebanese and British consumers: Extending UTAUT2 with security, privacy, and trust. *Technology in Society, 59*, 101151.

[77] Mou, J., Shin, D.-H., & Cohen, J. (2017). Understanding trust and perceived usefulness in the consumer acceptance of an e-service: a longitudinal investigation. *Behaviour & Information Technology, 36*(2), 125-139.

[78] Moussawi, S., Koufaris, M., & Benbunan-Fich, R. (2022). The role of user perceptions of intelligence, anthropomorphism, and self-extension on continuance of use of personal intelligent agents. *European Journal of Information Systems*, 1–22. https://doi.org/10.1080/0960085x.2021.2018365

[79] Munoz-Leiva, F., Climent-Climent, S., & Liébana-Cabanillas, F. (2017). Determinants of intention to use the mobile banking apps: an extension of the classic TAM model. *Spanish Journal of Marketing - ESIC, 21*(1), 25-38.

[80] Natarajan, T., Balasubramanian, S. A., & Kasilingam, D. L. (2018). The moderating role of device type and age of users on the intention to use mobile shopping applications. *Technology in Society, 53*, 79-90.

[81] Nguyen, Y.T.H., Tapanainen, T., & Nguyen, H.T.T. (2022). Reputation and its consequences in fintech services: The case of mobile banking. *International Journal of Bank Marketing, 40*(7), 1364–1397.

[82] Noreen, U., Shafique, A., Ahmed, Z., & Ashfaq, M. (2023). Banking 4.0: Artificial intelligence (AI) in banking industry & consumer's perspective. Sustainability, 15(3682).

[83] Ofori, K. S., Boateng, H., Okoe, A. F., & Gvozdanovic, I. (2017). Examining customers' continuance intentions towards internet banking usage. *Marketing Intelligence and Planning, 35*(6), 756-773.

[84] Oliver, R.L. (1980). A cognitive model for the antecedents and consequences of satisfaction. *Journal of Marketing Research, 17*(4), 460–469.

[85] Pattanayak, D., Koilakuntla, M., & Punyatoya, P. (2017). Investigating the influence of TQM, service quality, and market orientation on customer satisfaction and loyalty in the Indian banking sector.

International Journal of Quality and Reliability Management, 34(3), 362–377. https://doi.org/10.1108/ijqrm-04-2015-0057

[86] Payne, E.H.M., Peltier, J., & Barger, V.A. (2021). Enhancing the value co-creation process: Artificial intelligence and mobile banking service platforms. *Journal of Research in Interactive Marketing, 15*(1), 68–85.

[87] Peng, C., OuYang, Z., & Liu, Y. (2019). Understanding bike sharing use over time by employing extended technology continuance theory. *Transportation Research Part A: Policy and Practice, 124*, 433–443.

[88] Pengnate, S.F., & Sarathy, R. (2017). An experimental investigation of the influence of website emotional design features on trust in unfamiliar online vendors. *Computers in Human Behavior, 67*, 49–60.

[89] Pham, H.C., Duong, C.D., & Nguyen, G.K.H. (2024). What drives tourists' continuance intention to use ChatGPT for travel services? A stimulus-organism-response perspective. *Journal of Retailing and Consumer Services, 78*, 103758.

[90] Rahmani, D., Zeng, C., Chen, M., Fletcher, P., & Goke, R. (2023). Investigating the effects of online communication apprehension and digital technology anxiety on organizational dissent in virtual teams. *Computers in Human Behavior, 144*. https://doi.org/10.1016/j.chb.2023.107719

[91] Rahi, S., Alghizzawi, M., & Ngah, A.H. (2022). Factors influence user's intention to continue use of e-banking during COVID-19 pandemic: The nexus between self-determination and expectation confirmation model. *EuroMed Journal of Business, 18*(3), 380–396.

[92] Rahi, S., Khan, M.M., & Alghizzawi, M. (2021). Extension of technology continuance theory (TCT) with task technology fit (TTF) in the context of internet banking user continuance intention. *International Journal of Quality & Reliability Management, 38*(4), 986–1004.

[93] Rezvani, A., Khosravi, P., & Dong, L. (2017). Motivating users toward continued usage of information systems: Self-determination theory perspective. *Computers in Human Behavior, 76*, 263–275.

[94] Riad, M. I., Jaradat, M., Moh, Z., & Smadi, A. (2013). Applying the technology acceptance model to the introduction of mobile healthcare information systems. *International Journal of Behavioural and Healthcare Research*, 4(2), 123–143.

[95] Ringle, C.M., Sarstedt, M., & Straub, D.W. (2012). Editor's comments: A critical look at the use of PLS-SEM in "MIS Quarterly". *MIS Quarterly, 36*(1), iii–xiv.

[96] Ringle, C.M., Wende, S., & Becker, J.M. (2015). SmartPLS 3. *SmartPLS GmbH, Boenningstedt*.

[97] Samar, R., & Mazuri, A.G. (2019). Integration of DeLone and McLean and self-determination theory in internet banking continuance intention context. *International Journal of Accounting and Information Management, 27*(3).

[98] Sarkar, S., & Khare, A. (2018). Influence of expectation confirmation, network externalities, and flow on use of mobile shopping apps. *International Journal of Human–Computer Interaction*, 1-12.

[99] Schierz, P. G., Schilke, O., & Wirtz, B. W. (2010). Understanding consumer acceptance of mobile payment services: An empirical analysis. *Electronic Commerce Research and Applications, 9*(3), 209-216.

[100] Scott. D. & Usher, R. (2004). Researching education: Data, methods, and theory in educational enquiry. New York: Continuum.

[101] Shaikh, A.A., & Karjaluoto, H. (2015). Mobile banking adoption: A literature review. *Telematics and Informatics, 32*(1), 129–142.

[102] Shams, G., Rehman, M.A., Samad, S., & Oikarinen, E.-L. (2020). Exploring customer's mobile banking experiences and expectations among generations X, Y, and Z. *Journal of Financial Services Marketing, 25*, 1–13.

[103] Shang, D., & Wu, W. (2017). Understanding mobile shopping consumers' continuance intention. *Industrial Management & Data Systems, 117*(1), 213-227.

[104] Shankar, A., Jebarajakirthy, C., & Ashaduzzaman, M. (2020). How do electronic word of mouth practices contribute to mobile banking adoption? J*ournal of Retailing and Consumer Services, 52*(June 2019), 101920. https://doi.org/10.1016/j.jretconser.2019.101920

[105] Shaw, N., & Sergueeva, K. (2019). The non-monetary benefits of mobile commerce: Extending UTAUT2 with perceived value. *International Journal of Information Management, 45*, 44–55.

[106] Simmering, M.J., Fuller, C.M., Richardson, H.A., Ocal, Y., & Atinc, G.M. (2015). Marker variable choice, reporting, and interpretation in the detection of common method variance: A review and demonstration. *Organizational Research Methods, 18*(3), 473–511.

[107] Singh, S., & Srivastava, R. K. (2018). Predicting the intention to use mobile banking in India. *International Journal of Bank Marketing, 36*, 357–358. https://doi.org/10.1108/IJBM-12-2016-0186

[108] Sinha N, Singh N (2022) Revisiting expectation confirmation model to measure the effectiveness of multichannel bank services for elderly consumers. Int J Emerg Mark. https://doi.org/10.1108/ijoem-03-2021-0361

[109] Sun, Y., Li, S., & Yu, L. (2021). The dark sides of AI personal assistant: effects of service failure on user continuance intention. *Electronic Markets, 32*(1), 17-39.

[110] Susanto, A., Chang, Y., & Ha, Y. (2016). Determinants of continuance intention to use the smartphone banking services: an extension to the expectation-confirmation model. *Industrial Management & Data Systems, 116*(3), 508-525.

[111] Szymanski, D.M., & Henard, D.H. (2001). Customer satisfaction: A meta-analysis of the empirical evidence. *Journal of the Academy of Marketing Science, 29*(1), 16–35.

[112] Tang Y, Jiang, S, Lee JC (2022). Continuous usage intention of artificial intelligence (AI)-enabled mobile banking: a preliminary study. In: 2022 2nd international conference on economic development and business culture. Atlantis Press. pp. 135–139

[113] Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: a test of competing models. *Information Systems Research, 6*(2), 144-176.

[114] Tran, H. T. T., & Corner, J. (2016). The impact of communication channels on mobile banking adoption. *International Journal of Bank Marketing, 34*(1), 78-109.

[115] Tran, L.T.T., Pham, L.M.T., & Le, L.T. (2019). E-satisfaction and continuance intention: The moderator role of online ratings. *International Journal of Hospitality Management, 77*, 311–322.

[116] Trauth, E. (2011). What can we learn from gender research? Seven lessons for business research methods. The Electronic Journal of Business Research Methods, 9(1), 1-9.

[117] Tsai, H.-T., Chien, J.-L., & Tsai, M.-T. (2014). The influences of system usability and user satisfaction on continued Internet banking services usage intention: empirical evidence from Taiwan. *Electronic Commerce Research, 14*(2), 137-169.

[118] Twum, K.K., Kosiba, J.P.B., Hinson, R.E., Gabrah, A.Y.B., & Assabil, E.N. (2023). Determining mobile money service customer satisfaction and continuance usage through service quality. *Journal of Financial Services Marketing, 28*, 30–42. https://doi.org/10.1057/s41264-021-00138-5

[119] Venkatesh, V., & Davis, F. D. (1996). A model of the antecedents of perceived ease of use: Development and test. *Decision Sciences, 27*(3), 451-481.

[120] Venkatesh, V., & Davis, F.D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204.

[121] Wu, B., & Chen, X. (2017). Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task-technology fit (TTF) model. *Computers in Human Behavior, 67*, 221–230.

[122] Xue, M., Saravanan, V., & Montenegro-Marin, C. E. (2021). Cloud computing with AI for banking and e-commerce applications. *The Electronic Library, 39*(4), 539-552.

[123] Yang, Y., Asaad, Y., & Dwivedi, Y. (2017). Examining the impact of gamification on intention of engagement and brand attitude in the marketing context. *Computers in Human Behavior, 73*, 459-469.

[124] Yin, L.X., & Lin, H.C. (2022). Predictors of customers' continuance intention of mobile banking from the perspective of the interactivity theory. *Economic Research-Ekonomska Istraživanja, 35*(1), 6820–6849.

[125] Yuan, S., Liu, Y., Yao, R., & Liu, J. (2016). An investigation of users' continuance intention towards mobile banking in China. *Information Development, 32*(1), 20–34.

[126] Zailani, S., Iranmanesh, M., Nikbin, D., & Beng, J.K.C. (2015). Determinants of RFID adoption in Malaysia's healthcare industry: Occupational level as a moderator. *Journal of Medical Systems, 39*(1), 172.

[127] Zhang, T., Lu, C., & Kizildag, M. (2018). Banking "on-the-go": Examining consumers' adoption of mobile banking services. International Journal of Quality and Service Sciences, 10(open in a new window)(3(open in a new window)), 279–295. https://doi.org/10.1108/IJQSS-07-2017-0067

Journal of Information Systems Engineering and Management
2025, 10(3)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

[128] Zhou, W., Tsiga, Z., Li, B., Zheng, S., & Jiang, S. (2018). What influences users' e-finance continuance intention? The moderating role of trust. *Industrial Management & Data Systems, 118*(8), 1647–1670. https://doi.org/10.1108/imds-12-2017-0602