The effect of artificial intelligence on the intention to use bank mobile applications (case study: private banks)

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ABSTRACT:

Purpose – The development of mobile technology has changed the traditional financial industry and banking sector. While traditional banks have adopted artificial intelligence (AI) techniques to deepen the development of mobile banking applications (apps), the current literature lacks research on the use of AI-based constructs to explore users' mobile banking app adoption intentions. To fill this gap, based on stimulus-organism-response (SOR) theory, two AI feature constructs as stimuli are considered, namely, perceived intelligence and anthropomorphism. This study then develops a research model to investigate how intelligence and anthropomorphism affect task-technology fit (TTF), perceived cost, perceived risk and trust (organism), which in turn influence users' AI mobile banking app adoption (response).

Design/methodology/approach – This study used a convenience nonprobability sampling approach; a total of 451 responses were collected to examine the model. The partial least squares technique was utilized for data analysis.

Findings – The results show that intelligence and anthropomorphism increase users' willingness to adopt mobile banking apps through TTF and trust. However, higher levels of anthropomorphism enhance users' perceived cost. In addition, both intelligence and anthropomorphism have insignificant effects on perceived risk. The results provide theoretical contributions for AI-based mobile banking app adoption and offer practical guidance for bank planning to use AI to retain users.

Originality/value – Based on SOR theory, this study reveals that as features, AI-enabled intelligence and anthropomorphism help us further understand users' perceptions regarding cost, risk, TTF and trust in the context of AI-enabled app adoption intentions.

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1. Introduction

In recent years, the continuous penetration of mobile technology into the financial and banking industries has transformed the traditional banking service provision method into a new modern banking technology supported by the internet (Tran and Corner, 2016; Gupta *et al.*, 2019; Ajimon, 2018). In this context, the emergence of mobile banking and the study of its adoption are important to both users and banks (Cao *et al.*, 2014; Cao and Liu, 2018).

Mobile banking eliminates the physical limitations of daily banking activities, which allows users to conduct their banking business at the time and place of their choice (Hassan and Wood, 2020). In addition, users can conduct bank activities such as transferring funds, making investments, making payments, and checking account information periodically through mobile banking (Owusu Kwateng et al., 2019), which provides a fast and effective alternative to physical banking services (Merhi et al., 2019). Additionally, banks provide a high-efficiency (Malaquias and Hwang, 2019) and lucrative banking platform (Zhang et al., 2018), and continuous innovation in mobile banking services attracts users, maintains a comparative advantage over competition, and achieves a return on investment in technology (Sharma et al., 2017).

A key aspect of successful mobile banking implementation is user adoption and acceptance (Shumaila, 2012). The existing mobile banking literature indicates that since the demand for intelligent and personalized services has increased in the banking sector, artificial intelligence (AI) techniques have become critical (Loureiro et al., 2020; Milana and Ashta, 2021). AI now plays a significant role in mobile banking adoption (Darby, 2016; Manser Payne et al., 2018, 2021; Suhartanto et al., 2021; Yussaivi et al., 2021). The term AI refers to using intelligent machine performance and humanlike behavior to help users and increase their experience in using banking services (Prentice et al., 2019). AI can help users complete tasks by understanding their background, answering their inquiries and providing them with assistance and value (Lin et al., 2021). For example, JD.com Instant Messaging Intelligence (JIMI) of Jingdong (JD) Finance began to provide customers with intelligent consulting services in October 2015. In the face of various problems that may occur, JIMI must respond flexibly and even guide users' behaviors during the interaction. JIMI can understand user needs based on context, initiate machine learning, identify customer emotions, and provide personalized services (Zhu, 2018).

The evolution from traditional mobile banking apps to today's smart apps is the most intuitive embodiment of the development of AI (Lin et al., 2021). In AI-enabled mobile banking applications (apps), when users seek services, artificially intelligent service programs intelligently process data, analyze users' emotions and use natural language to provide personalized services and transactions (Zhu, 2018). AI can also provide anthropomorphic financial services, which makes mobile banking services more intelligent and human (Jiang, 2018; Wang, 2017). Therefore, it is critical to understand the role AI plays in mobile banking apps. The understanding and perception of humans that AI brings represent the key differences between artificially intelligent services and other systems, namely the two key AI features of intelligence and anthropomorphism (Lin et al., 2021; Moussawi and Koufaris, 2019; Moussawi et al., 2020). Specifically, intelligence reflects a system (i.e. mobile banking apps in this study) with efficient and autonomous behavior that can help users address financial services or tasks. Anthropomorphism signifies a system that behaves similar to humans when processing a service or task (Lin et al., 2021). In the extant literature, several studies have explored mobile banking in the AI context but ignored how AI features in app evolution affect user adoption intentions (Manser Payne et al., 2018, 2021; Suhartanto et al., 2021). Hence, in this study, the intelligence and anthropomorphism constructs are considered the foremost AI features to explore user intention in adopting AI-enabled mobile banking apps. Moreover, the existing literature has shown that mobile banking users often consider functional and technical reasons (Gupta et al., 2019), including task-technology fit (TTF) (Zhou et al., 2010; Baabdullah et al., 2019; Tam and Oliveira, 2016a, b, 2019), perceived cost (Owusu Kwateng et al., 2019; Haider et al., 2018; Merhi et al., 2019) and perceived risk (Mohammadi, 2015; Mun~oz-Leiva et al., 2017; Priya et al., 2018; Siyal et al., 2019), which may influence the intention to adopt mobile banking. In addition to the functional aspect, scholars have pointed out that user psychology should be considered in user adoption, the most important aspect of which is user trust (Mehrad and Mohammadi, 2017; Sharma et al., 2017; Gupta *et al.*, 2019; Malaquias and Hwang, 2019; Sharma and Sharma, 2019), which is critical for mobile banking. Users who believe that mobile banking is trustworthy may be more willing to share personal information to facilitate adoption (Mehrad and Mohammadi, 2017; Sinha and Mukherjee, 2016; Zhang *et al.*, 2018; Siyal *et al.*, 2019; Hassan and Wood, 2020; Singh and Srivastava, 2018). Today, AI technology has penetrated mobile banking. However, extant studies on mobile banking often treat AI development as a background cause or role (Manser Payne *et al.*, 2018, 2021; Suhartanto *et al.*, 2021) and how the AI features of intelligence and anthropomorphism affect users' perceptions of the functional level (i.e. TTF, perceived cost, risk) and psychological level (i.e. trust) of mobile banking apps remains unknown, requiring further exploration and examination.

With the above backdrop, a research question is then proposed: Do AI-based constructs (i.e. perceived intelligence and anthropomorphism) influence mobile banking app adoption intentions through the functional level (i.e. TTF, perceived cost, risk) and psychological level (i.e. trust), and if so, how? To answer this question, we attempt to build upon stimulus- organism-response (SOR) theory (Mehrabian and Russell, 1974; Islam *et al.*, 2020) to develop a research model and corresponding hypotheses. The details of SOR theory are further explained in Section 2.1. A survey research method is employed to collect 451 samples with a partial least squares (PLS) technique utilized to examine the model and hypotheses. Studying users' willingness to adopt mobile banking with intelligence and anthropomorphism constructs expands the current knowledge of mobile banking in the AI context. The remainder of this paper is organized as follows. In the next section, we review the related literature concerning mobile banking adoption. Section 3 develops a research model and proposes the corresponding hypotheses. Section 4 describes the research method and design. Then, we analyze the model and show the statistical results in Section 5. Section 6 discusses and synthesizes the results and findings of this study. Finally, we conclude with the limitations of this study and provide directions for future research.

2. Theoretical background and literature review

2-1. Theories in mobile banking research

A key aspect of the successful implementation of mobile banking is user adoption (Shumaila, 2012). Therefore, research on mobile banking has investigated the factors and motivations that influence adoption intention (e.g. Cao *et al.*, 2014; Cao and Liu, 2018; Tam and Oliveira, 2017). Scholars have shown that the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT) are the most commonly used in the existing literature to study mobile banking (Shaikh and Karjaluoto, 2015; Gupta and Arora, 2017). However, these theories have been criticized for failing to consider the specific characteristics of technology (e.g. Cho *et al.*, 2019) and how these technological characteristics arouse users' assessments and reactions to the technology. To understand users' adoption of AI-enabled mobile banking, we should consider the characteristics of AI technology perceived by users that influence their internal state, which leads to individuals' approach- and-avoidance behaviors. In this regard, we attempt to utilize SOR theory (Mehrabian and Russell, 1974; Islam *et al.*, 2020) as an overarching theoretical basis to explore user adoption of AI mobile banking apps. SOR theory is more appropriate for explaining AI-enabled mobile banking than the TAM or UTAUT because user adoption involves various stimuli (AI features) that users are exposed to and user assessments of the AI (Cho *et al.*, 2019).

SOR theory originated from environmental psychology and has been widely used in previous studies to reconnoiter user behavior in the mobile app setting (e.g. Chen and Yao, 2018; Ashraf *et al.*, 2021; Wu *et al.*, 2021). Specifically, stimulus refers to a collection of attributes that affect user perception. Organism expresses internal processing mechanisms and evaluations of users. Response is an outcome of users' reactions to their personal assessment (Mehrabian and Russell, 1974; Islam *et al.*, 2020). Based on SOR theory, while interacting with AI-enabled mobile banking apps, we consider how AI features (i.e. perceived intelligence and anthropomorphism) as stimuli shape users' functional evaluation (i.e. TTF, perceived cost, risk) and psychological evaluation (i.e. trust) (organism), which subsequently affect mobile banking app adoption intention (response).

2-2. Effect of AI on mobile banking

As a leading-edge technology, AI has been reported to have a significant influence on various business domains, such as finance and banking (Milana and Ashta, 2021; Loureiro *et al.*, 2020), marketing, and retailing (Huang and Rust, 2020; Capatina *et al.*, 2020; Guha *et al.*, 2021), tourism and hospitality (Ivanov and Webster, 2020; Li *et al.*, 2019) and operation management (Chakraborty and Boral, 2017; Turner *et al.*, 2019). Specifically, AI is defined as machines that exhibit aspects of human intelligence (Huang and Rust, 2020, 2021). Similar to humans, AI models perform cognitive tasks through computers and machines based on automation, big data and machine learning to achieve established goals and tasks (Prentice *et al.*, 2019). AI has reshaped business processes, products and services, and user experience. For example, in marketing and retailing, AI technology provides customers with personalized offers to increase customer shopping experience and engagement (Grewal *et al.*, 2021). In the finance and banking sector, autonomous AI systems without human involvement provide opportunities for banks to improve speed, accuracy, and efficiency in online banking (Kaya, 2019). Researchers have also shown that AI can facilitate real-time identification processing by banks to avoid fraudulent behaviors (e.g. credit and financial statement fraud) in online banking transactions (Kaya, 2019; Konigstorfer and Thalmann, 2020; Ricceri *et al.*, 2021). Luo *et al.* (2020) indicated that AI technology could promote the online banking service level and increase the security of traditional online banking systems.

With the vigorous development of mobile technology, the practical connection between AI and mobile banking has been further strengthened, and research on the relationship between the two has become more valuable. Scholars have pointed out that AI, as a key aspect of mobile banking innovation (Huang *et al.*, 2021), can better develop users' experience and increase the efficiency of banking services, thereby creating deeper user relationships (Xing, 2017; Wang, 2017; Jiang, 2018; Manser Payne *et al.*, 2018; Huang and Rust, 2020; Lin *et al.*, 2021). When using AI-enabled mobile banking apps, users who encounter difficulties can seek the help of artificially intelligent services in a timely manner (Zhu, 2018). AI-enabled mobile banking apps can intelligently use natural language and formulate precise queries to assist humans during interactions and handle similar problems uniformly. The goals are to generate standardized, consistent, and reliable results

(Selley *et al.*, 1997; Manser Payne *et al.*, 2018), improve efficiency (Lin *et al.*, 2021), and reduce the risk of human customer service subjective judgment errors. In addition, the apps are able to provide personalized benefits to identify and match different descriptions of different users with the same problem (Wiegard and Breitner, 2019; Manser Payne *et al.*, 2018, 2021) and provide the benefits of rationalization and technical visualizations fully reflect anthropomorphism (Li *et al.*, 2019). Table 1 summarizes the research on the application of AI in mobile banking.

2-4.AI features as stimuli

The measurements for AI features primarily focus on users' perceptions, which are different from their perceptions of other systems due to the personalized, intelligent, and anthropomorphic behavior of AI applications (Huang and Rust, 2020; Grewal *et al.*, 2021; Mishra *et al.*, 2021). Moussawi and Koufaris (2019) adopted a systematic approach to conclude that perceived intelligence and anthropomorphism are two key characteristics of AI-enabled systems. Then, they developed a reliable and valid scale to measure users' perceptions

Authors	Independent variable	Dependent variable	Main findings
Manser Payne *et al.* (2018)	Need for service, quality of service, attitudes toward AI, relative advantage, security in specific mobile banking activities and perceived trust	Mobile banking usage and comfort using AI mobile banking services	Attitudes toward AI exert the strongest impact on comfort using AI services, followed by security, and trust in mobile banking Relative advantage plays the strongest role in mobile banking, followed by security, trust and attitude toward AI
Manser Payne *et al.* (2021)	Perceptions of AI service delivery and current bank service delivery, data security, service delivery configuration benefits, safety perceptions of mobile banking services	Assessment of AI mobile banking	AI service delivery and current bank service delivery have a significant and positive influence on assessment of AI mobile banking AI service delivery fully mediates the relationship between safety and assessment of AI mobile banking
Suhartanto *et al.* (2021)	Need for service, quality of service, attitude toward AI, relative advantage, security, perceived trust and religiosity	AI-enabled mobile banking loyalty	Service quality, attitude toward AI and trust are key factors that foster millennial loyalty toward AI-enabled mobile banking
Lin *et al.* (2021)	Perceived anthropomorphism and intelligence, performance and effort expectancy, and facilitating conditions	Mobile banking continuance intention	Both perceived anthropomorphism and intelligence can increase users' continuance intention via performance expectancy and facilitating conditions

Regarding the AI system's behavior and ability in terms of intelligence and anthropomorphism. This scale for the measurement of AI has been validated and applied to several subsequent AI-powered technology adoption studies (e.g. Moussawi *et al.*, 2020; Pillai and Sivathanu, 2020; Balakrishnan and Dwivedi, 2021). Specifically, perceived intelligence is defined as the extent to which the behavior of mobile banking apps is perceived as able to provide effective output through AI to complete tasks and generate and process natural language. AI-enabled systems are designed to have humanlike images and titles or simulate human emotions and behaviors (Lin *et al.*, 2020; Moussawi and Koufaris, 2019). These humanlike characteristics are referred to as anthropomorphism (Moussawi and Koufaris, 2019; Moussawi *et al.*, 2020). Lin *et al.* (2021) followed the suggestion recommended by Moussawi and Koufaris (2019) and Moussawi *et al.* (2020) to use perceived intelligence and anthropomorphism as the primary AI features to explore users' perceptions concerning AI-enabled mobile banking. According to the aforementioned studies and SOR theory, we deem perceived intelligence and anthropomorphism as stimuli of AI mobile banking apps to predict user adoption behavior.

2-5. Functional and psychological factors as organism

Scholars have shown that resistance to innovation adoption stems mainly from functional and psychological perspectives (Ram and Sheth, 1989; Huang *et al.*, 2021). Based on Ram and Sheth's (1989) definitions, functional aspects involve three main factors: TTF, perceived cost and risk. In the mobile banking context, scholars believe that risk determines users' perception of financial loss suffered, privacy being violated, or personal data exploited, which is a dominant predictor for mobile banking adoption (Lie'bana-Cabanillas *et al.*, 2016; Mohammadi, 2015; Munoz-Leiva *et al.*, 2017; Priya *et al.*, 2018; Siyal *et al.*, 2019). In addition, research has indicated that exploring users' perceptions of cost is important because it determines the predictive ability for understanding and learning to use mobile banking apps (Hanafizadeh *et al.*, 2014; Haider *et al.*, 2018; Owusu Kwateng *et al.*, 2019; Merhi *et al.*, 2019). Moreover, existing studies have adopted the TTF model to explore users' evaluations of mobile banking adoption (Oliveira *et al.*, 2014; Zhou *et al.*, 2010; Baabdullah *et al.*, 2019; Tam and Oliveira, 2016a, b, 2019). Researchers have confirmed that integrating multiple factors is helpful to maximize the explanatory power of user adoption intention (Zhou *et al.*, 2010; Baabdullah *et al.*, 2019; Tam and Oliveira, 2019). Thus, after being combined with risk, cost, and TTF in this study, functional factors (organismic experiences) are further considered to predict users' intentions to use AI mobile banking apps. In terms of psychological perspective, the existing literature indicates that the most important source of psychological resistance is the trust problem that mobile banking innovation brings to users (Mehrad and Mohammadi, 2017; Sharma *et al.*, 2017; Gupta *et al.*, 2019; Malaquias and Hwang, 2019; Sharma and Sharma, 2019). Sarkar *et al.* (2020, p. 286) also pointed out that trust is the most significant predictor of m-commerce adoption, as it strongly determines its success. In addition, Bedu´e and Fritzsche (2021) showed that an important path leading to better AI-based adoption is trust-building, which is why we chose to trust as a main psychological factor (organism) in the model.

Moreover, the existing studies have independently tested several functional and psychological factors that influence users' adoption of mobile banking (Gupta and Arora, 2017), but no studies have combined them into a single model. The literature in the field of social psychology believes that the factors that promote and prevent adoption may not only be opposites. Mobile banking can also be explained by behavioral reasoning theory, which allows simultaneous testing of the influence of adoption and resistance factors in a model (Gupta and Arora, 2017). In this regard, this study investigates the factors (organism) that influence users' adoption of mobile banking apps by integrating the functional and psychological aspects, corresponding to the selection of TTF, perceived cost, risk (functional factors) and trust (psychological factors).

2-6. Research gap in AI-enabled mobile banking

Given the emergence of the AI service of mobile banking, this study extends the current view of mobile banking into the AI-powered evolution of mobile banking apps. Although a majority of extant studies have discussed the role of AI in users' adoption or usage of mobile banking (Manser Payne *et al.*, 2018, 2021; Suhartanto *et al.*, 2021), little attention has been given to exploring how AI features (intelligence and anthropomorphism) influence users' functional and psychological evaluations in the context of AI-based mobile banking. To fill this gap, we build upon SOR theory to develop a research model by treating intelligence and anthropomorphism as stimuli and investigate their impacts on TTF, risk, perceived cost (functional organism), and trust (psychological organism), which in turn affect users' intention to adopt AI-enabled mobile banking apps (response).

Moreover, users in different countries may show different perceptions and reactions to banking services (Malaquias and Hwang, 2019; Zhang *et al.*, 2018). A contextualized investigation at the national level can offer fresh insights that contribute to the creation of new knowledge in new and less understood contexts (Ashraf *et al.*, 2021). In existing AI-enabled financial or banking research, most of the extant studies focus on the USA (Manser Payne *et al.*, 2018, 2021; Belanche *et al.*, 2019), UK (Belanche *et al.*, 2019; Bholat and Susskind, 2021), or Australia (Argus and

Samson, 2021). However, research on users' perception of AI banking services in the context of Iran remains unexplored. Thus, this study attempts to emphasize Iranese users and explore their cognition in adopting AI- enabled mobile banking apps through functional and psychological aspects. This helps increase country-specific understanding of how AI technology shapes mobile banking services.

3. Development of the research model

The proposed model is shown in Figure 1. Specifically, based on SOR theory, we explore how perceived intelligence and anthropomorphism (stimuli) influence users' functional and psychological evaluations (organism), which in turn affect their intentions to adopt mobile banking apps (response). In particular, we distinguish the organism by functional and psychological aspects. At the functional level, we select TTF, perceived cost and risk as variables. Concerning the psychological level, we consider the trust variable.

3-1.Perceived intelligence and anthropomorphism

In this study, the two key AI-based characteristics of mobile banking, namely, intelligence and anthropomorphism, involve the understanding of intelligence and the perceptions of humans (Lin *et al.*, 2020, 2021). In AI-enabled mobile banking apps, users can enter questions, and AI service programs can quickly search for keywords and immediately provide standardized answers or even predict the search terms users want and automatically fill them in, present personalized search results, and remember and learn from previous search behaviors. At the same time, mobile banking's AI customer service avatars, names and interactions with users are similar to those of real people (Moussawi *et al.*, 2020). However, perceived intelligence and perceived anthropomorphism are not completely different and unrelated structures. Moussawi *et al.* (2020) mentioned that when users employ AI-enabled service, their display of intelligent characteristics may also cause users to regard it as caring, loving, respectful or interesting. The communication of AI services makes people feel that the

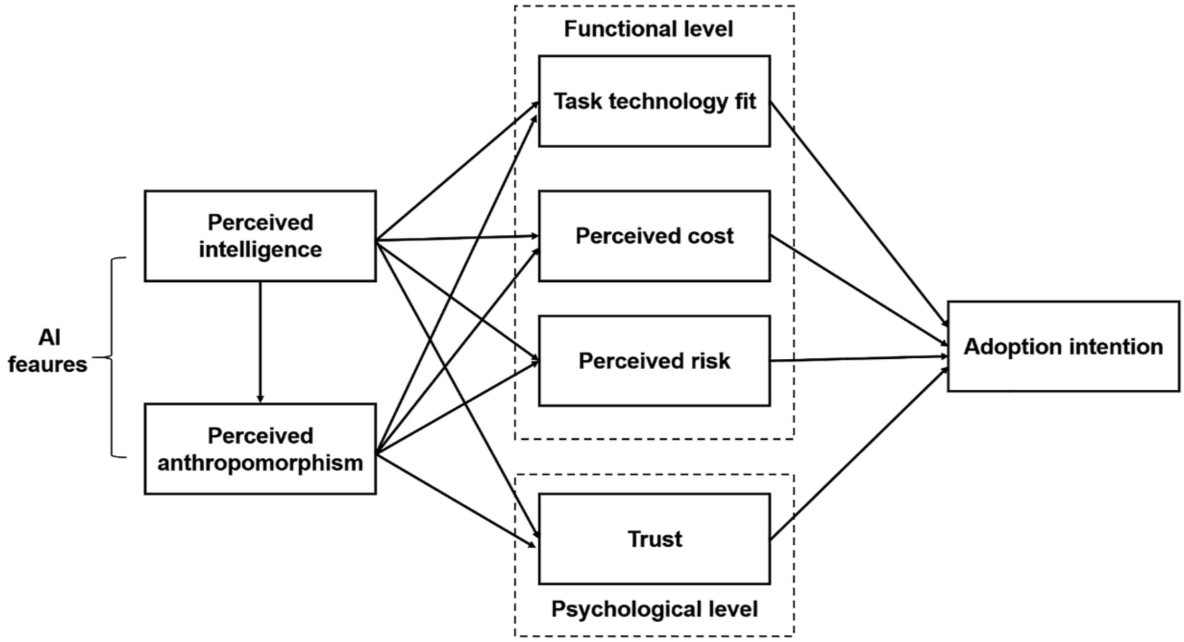

Figure 1. The research model

applications are anthropomorphic and have a deeper understanding (Mishra et al., 2021; Moussawi et al., 2020; Moussawi and Koufaris, 2019) of users' needs. Therefore, an increase in perceived intelligence may also increase perceived anthropomorphism. We hypothesize that

H1. Perceived intelligence can promote perceived anthropomorphism.

3-2.Task technology fit

In AI-enabled mobile banking apps, service programs can capitalize on existing AI technologies to provide personalized services to users (Manser Payne *et al.*, 2018). For example, the answers powered by AI can accurately match the questions that mobile banking users ask; instead of making users ask questions multiple times to obtain the answers they need via multiple rounds of interaction, mobile banking users acquire answers more quickly through the use of AI programs or services, causing them to perceive the matching degree of technology and tasks differently compared with traditional manmade customer service. In addition, AI mobile banking apps are designed to have human-like appearances and can simulate human emotions and behaviors (Lin *et al.*, 2020). These humanlike features of AI services enable users to complete mobile banking transaction tasks as if they were interacting with real people (Lin *et al.*, 2021). Mohd Thas Thaker *et al.* (2019) mentioned that anthropomorphic features could benefit users using technology to accomplish tasks. Here, tasks refer to "actions" performed by individuals to convert inputs into outputs, and technology is defined as "tools" used by individuals to perform tasks. TTF assumes that users tend to use mobile banking to obtain benefits such as improved performance because TTF means that technological functionality improves smooth task execution and reduces the time required to perform banking services such as funds transfer, thereby improving efficiency. If an AI-enabled mobile banking app provides technologies highly compatible with the task the user currently needs to complete, the user will perceive the service as useful for completing the task (Baabdullah *et al.*, 2019; Tam and Oliveira, 2016a, b, 2019), thereby increasing their adoption intention. Therefore, we assume the following:

H2. Perceived intelligence can improve TTF.

H3. Perceived anthropomorphism can improve TTF.

H4. TTF can increase the adoption intention of mobile banking.

3-3. Perceived cost

Perceived cost has an impact on users' technology adoption. Perceived cost is regarded as a personal cognitive trade-off analysis. When users perceive that the value provided by mobile banking services is higher than their costs, the users will be more inclined to adopt mobile banking (Owusu Kwateng *et al.*, 2019). In the field of mobile banking, the perceived cost is considered the main obstacle to adoption and can be regarded as the cost users incur when adopting mobile banking, which is the degree to which users believe that the costs involved in adopting mobile banking are higher than the costs of other available options (Haider *et al.*, 2018). Defined in economic terms as including search, information, bargaining, decision- making, and execution, costs are important drivers of users' willingness to adopt (Lin *et al.*, 2020). In using AI-enabled mobile banking apps, the intelligent anthropomorphic characteristics of services can reduce the cost of waiting in line for users. AI services simulate manual customer service by using AI to provide standardized answers when first- time users ask questions without the need to wait in line. On the other hand, the conversion from traditional mobile banking customer service to AI customer service requires little energy and time to learn because manual customer service simulation does not require much energy or time on users. In contrast, personalized functions are intended to meet users' personal needs. Lin *et al.* (2020) found that the benefits obtainable through the use of AI devices greatly reduce transaction costs. Therefore, the perceived cost of mobile banking apps powered by AI will be effectively reduced, and the perceived cost of developing mobile banking will reduce its adoption (Singh and Srivastava, 2018). Therefore, we hypothesize that

H5. Perceived intelligence reduces perceived cost.

H6. Perceived anthropomorphism reduces perceived cost.

H7. Perceived costs reduce the adoption intention of mobile banking.

3-4. Perceived risk

Perceived risk is the degree of uncertainty users have regarding their ability to achieve the expected results and may even involve losses caused by mismatches between user demand and technology when using mobile banking (Hassan and Wood, 2020; Mortimer *et al.*, 2015; Munoz-Leiva *et al.*, 2017). These risks include financial, performance, and privacy risks. Specifically, financial risk is a fundamental technology-driven risk that may be related to defects in the mobile banking operating system. Many users do not use mobile banking because they are afraid of losses due to transaction errors. The AI development of mobile banking apps can enhance users' perceptions of intelligence, and advancements in the guarantees of technology have reduced the number of unsafe incidents and risks, including the possibility of financial risks. Performance risk is considered the fear of not being able to complete a transaction within a reasonable time. In the past, users were generally concerned with the inefficient workings of manual customer service (Mohammadi, 2015). Compared with manual transactions, AI mobile banking apps could better meet users' personal performance needs (Manser Payne *et al.*, 2018). The most frequently discussed risk involves the misuse of user data, which introduces privacy risks and can lead to fraud, theft, or other crimes (Darby, 2016). To a certain extent, the intelligence of mobile banking apps reduces the perception of risk that occurs when users share personal information with real people, and sufficient intelligence also enhances users' perceptions of the degree of protection applied to all data collected during an interaction with an app. If the user's needs and the actual behavior of mobile banking technology are inconsistent and fail to provide the expected results, the risks will exceed users' perceptions, possibly causing losses, which will reduce users' willingness to adopt mobile banking (Wiegard and Breitner, 2019). We can hypothesize the following:

H8. Perceived intelligence reduces risk.

H9. Perceived anthropomorphism reduces risk.

H10. Risk reduces the adoption intention of mobile banking.

3-5.Trust

Today, the intelligent anthropomorphism characteristics of AI have been studied in the fields of information systems (Moussawi *et al.*, 2020), marketing (Huang and Rust, 2020, 2021), and finance (Belanche *et al.*, 2019; Milana and Ashta, 2021). When AI-enabled mobile banking apps are regarded as respectful, interesting, friendly, and concerned with others, users will subjectively perceive AI technology as more reliable than conventional mobile banking apps. The addition of intelligence further ensures that mobile banking apps have fewer operating errors, thereby increasing trust in mobile banking (Moussawi and Koufaris, 2019). When users adopt mobile banking, trust provides an important foundation for successful interactions between users and AI services. Trust is an important factor in mobile banking research because it plays a vital role in shaping future interactions between two parties (Mehrad and Mohammadi, 2017; Sharma *et al.*, 2017; Gupta *et al.*, 2019; Malaquias and Hwang, 2019; Sarkar *et al.*, 2020). Trust can help individuals overcome the perception of uncertainty and allow them to build trust-based relationships with trustees through behaviors such as sharing personal information (Moussawi *et al.*, 2020). The intelligence of mobile banking apps is embodied in the aspects of autonomous efficiency, the ability to process and produce language, and the support and understanding of user needs (Lin *et al.*, 2021). Users can establish a sense of trust in mobile banking through their perceptions of these characteristics of intelligence. During interactions between users and AI mobile banking apps, because of the anthropomorphism component added to intelligent services, users will use any available information to make trust inferences about them through their perceptions of their intelligence and anthropomorphism characteristics, which rely on AI. When a mobile banking AI app completes the banking business, it is subliminally perceived as a real person (Lin *et al.*, 2021). Therefore, users will trust mobile banking apps more when they think the provided service is intelligent and anthropomorphic. Researchers have also shown that a lack of trust causes consumers to worry that their personal information or funds may be transferred to others without their knowledge, making them unwilling to use mobile banking for transactions (Gupta *et al.*, 2019; Owusu Kwateng *et al.*, 2019; Merhi *et al.*, 2019; Lie'bana- Cabanillas *et al.*, 2016; Sharma and Sharma, 2019). Therefore, we hypothesize that

H11. Perceived intelligence can promote trust.

H12. Perceived anthropomorphism can promote trust.

H13. Trust can promote the adoption of mobile banking.

Scholars have indicated that within SOR theory, the role of user internal evaluation (organism) may theoretically mediate stimuli and responses (Cho *et al.*, 2019; Chan *et al.*, 2017; Arora, 1982). In addition, based on Baron and Kenny's (1986) criteria concerning mediation, a mediating effect occurs in which an independent variable influences a dependent variable through an additional theoretically relevant variable. As we hypothesized before, in the AI context, the AI features of intelligence and anthropomorphism may affect users' intentions to adopt AI mobile banking apps through their perceptions and evaluations of TTF, cost spent, risk and trust. In other words, organismal experiences (i.e. functional and psychological factors proposed in this study) may mediate the relationship between stimuli (AI characteristics) and user response (adoption intention). The mediating effects of the model will be examined in Section 5.2.

4.Research method

4-1.Data collection and sample

This study uses a survey method to examine the model, and the target samples are users with AI-enabled mobile banking app experience in Iran.To ensure face and content validity, the questionnaire was reviewed by five experts who specialized in AI technology and mobile banking services to ensure that the survey items were clear, meaningful, and understandable. Then, the questionnaire was sent to thirty mobile banking users for pretesting to ensure that the wording of the questionnaire conformed to people's domestic language habits. In addition, to design a high-quality and reliable online survey, we followed Illum *et al.*'s (2010) and Belanche *et al.*'s (2019) suggestions to control the length of the questionnaire and keep it short. We also declared that the questionnaire is anonymous and that the data are only to be used for academic purposes to encourage the respondents to honestly complete the questionnaire.

Finally, this study used a convenience nonprobability sampling approach recommended by previous technology adoption studies (Lin *et al.*, 2021; Agyei *et al.*, 2020; Farah *et al.*, 2018; Afshan and Sharif, 2016) to collect samples.

Before formal data collection, we checked the same size requirement for PLS analysis of the proposed model. Based on the rule of thumb of 10 cases per indicator (Chin, 1998; Lee *et al.*, 2018), the minimum sample size needed for the model is 50 (the variables include up to five indicators in the model). We also ran the SPSS software application to calculate the minimum sample size (Faul *et al.*, 2009). As suggested by Campanelli *et al.* (2018) and Lee *et al.*
(2021), the settings of the software were an effect size of 0.15 (average value), a power level of 0.95, and a maximum allowed error of 0.05, which suggested that the minimum sample size needed for the model was 129. The finalized formal questionnaire was distributed using the online survey platform and advertised through several social networking platforms (e.g. Telegram) to ensure the randomness of the sample. A total of 451 valid samples were collected, which met the minimum sample size requirements. Hence, the sample size is considered acceptable for data analysis.

Moreover, we checked whether the responses were representative of the population and examined the nonresponse bias using an extrapolation method suggested by Armstrong and Overton (1977) and Liang and Shiau (2018). This method is based on the assumption that participants who respond later are more likely to be nonrespondents (Chen and Lee, 2022a). We compared the *t*-test results of the sample attributes (i.e. sex, age, education, profession, income, and frequency of using mobile banking apps) at the 5% significance level from the earliest 25% of collected samples and the latest 25% of collected samples. There were no significant differences between these two groups [sex (t =0.555; p =0.557), age (t =1.18; p =0.271), education (t =0.63; p =0.512), profession (t =0.335; p =0.797), income (t =0.972; p =0.352), and frequency (t =1.51; p =0.237)]. Thus, nonresponse bias was not a significant issue, and the representativeness of our samples was supported. Table 2 presents the demographics of the participants. In particular, we observed that our sample mainly includes full-time students who are relatively low-income people. Most likely, students do not have ample opportunities to carry out financial services (e.g. subscribing and purchasing funds) due to less disposable money, and so they may use mobile banking services with less frequency within a year.

4-2. Measurement

The model includes seven latent variables, including six independent variables (perceived intelligence, perceived anthropomorphism, TTF, perceived cost, risk, trust) and one dependent variable (intention to adopt mobile banking). The measurement items for each variable were selected based on the prior validated literature and were modified to fit the AI mobile banking context and assessed using a seven-point Likert scale. Specifically, we operationalized perceived intelligence and anthropomorphism based on Moussawi and Koufaris (2019) and Lin *et al.* (2021). Perceived intelligence (five items) is evaluated by asking respondents to comment on the efficiency and autonomy of using mobile banking apps. Perceived intelligence (five items) was assessed by requesting respondents to judge how similar to a person’s AI-enabled mobile banking apps behaved. TTF was measured using a five-item scale from Lin and Huang (2008) to estimate the perception that AI mobile banking apps match the respondents’ requirements. Perceived cost included three items adapted from Hanafizadeh *et al.* (2014) to measure how much AI mobile banking apps cost respondents to use. Perceived risk was operationalized with five items derived from Hassan and Wood (2020) that reflect the level of uncertainty associated with the results when utilizing AI mobile banking apps. Four items adapted from Hassan and Wood (2020) were used to assess trust, which refers to the extent to which respondents worry about the privacy of their personal

Table 2. Sample demographic information

Item		Number	Percentage
Sex	Male	142	31.42
	Female	309	68.58
Age	18 years and below	8	1.85
	19–25 years	297	65.71
	26–40 years	39	8.62
	41–50 years	84	18.69
	51–60 years	21	4.72
	Over years	2	0.41
Education background	Below high school	17	3.7
	High school and junior college	68	14.99
	Undergraduate course	344	76.18
	Postgraduate and above	22	5.13
Profession	Institutions/government workers	29	6.37
	Corporate staff	53	11.7
	Professional skilled worker	30	6.57
	Business/service industry	21	4.72
	Full-time student	257	56.88
	Retiree	11	2.46
	Other	50	11.29
Average monthly income in Rials (CNY)	49,999,999 or less	320	71.05
	5,000,000 to 99,999,999	88	19.51
	100,000,000 to 149,999,999	19	4.11
	150,000,000 to 199,999,999	10	2.26
	200,000,000 to 249,999,999	4	0.82
	250,000,000 to 299,999,999	3	0.62
	Over 300,000,000	7	1.64
Frequency of using mobile banking in the last year	Less than once every quarter	106	23.61
	Two or three times a quarter	104	23
	Two or three times a month	125	27.72
	Two or three times a week	75	16.63
	Every day	41	9.03

data and security of banking transactions in using AI mobile banking apps. In terms of adoption intention, we used four items adapted from Priya *et al.* (2018) to reflect whether respondents are likely to adopt AI mobile banking apps. Appendix shows the survey items of the variables and their references. Moreover, several control variables (i.e. age, education background, profession, income, and frequency of using mobile banking) were included in the research model since they may influence users in adopting mobile banking (Matsuo *et al.*, 2018; Lin *et al.*, 2021).

4-3.Common method bias

Since the data were self-reported, common method bias (CMB) may exist (Podsakoff *et al.*, 2003). Consequently, Harman's single-factor test (Harman, 1967) was adopted to test the CMB. The results showed that no single factor explained more than 50% of the total variance, implying that CMB was not a possible concern (Podsakoff *et al.*, 2003). In addition, the full collinearity test suggested by Kock (2015) was further used to examine CMB. The test indicated that the values of all the variance inflation factors ranged from 1.638 to 2.986. All of the values were lower than the threshold of 3.3. With the above evidence, CMB was not a significant issue in this study.

5. Data analysis

In this study, we employ a partial least squares (PLS) technique to test the proposed model. PLS is distribution-free (i.e. the estimation is unaffected by the complexity of the model, small sample size, or nonnormality of the data) and overcomes multicollinearity problems (Lee *et al.*, 2018, p. 27). In addition, there are three reasons for choosing PLS instead of covariance-based SEM (CB-SEM) for analysis. First, the model is complicated, as it includes seven constructs and thirteen hypotheses. Scholars have shown that PLS can handle more complex modeling than CB-SEM (Ringle *et al.*, 2012; Hair *et al.*, 2012, 2017; Moussawi *et al.*, 2020). Second, the model is a focused type (i.e. the number of exogenous latent variables is at least twice as high as the number of endogenous latent variables) (Hair *et al.*, 2012, p. 421), which is suitable for PLS (Hair *et al.*, 2012; Koubaa *et al.*, 2014; Lin *et al.*, 2021; Chen and Lee, 2022b). Conversely, CB-SEM is appropriate for explaining unfocused models (i.e. the number of endogenous latent variables is at least twice as high as the number of exogenous latent variables) (Hair *et al.*, 2012, p. 421). Third, this study is exploratory in nature since we did not have clear previous knowledge or empirical evidence from the existing mobile banking literature about the relationships of the constructs used in the AI context (Hair *et al.*, 2017; Campanelli *et al.*, 2018). Compared to CB-SEM, PLS is primarily for exploratory work (Ringle *et al.*, 2012; Hair *et al.*, 2012, 2017). SmartPLS 3 software (Ringle *et al.*, 2015) was utilized for data analysis.

5-1. Measurement model

An initial exploratory factor analysis (EFA) was performed to ensure that the seven proposed variables were different. The EFA loadings of each item exceeded the threshold value of 0.4, ranging from 0.738 to 0.891 (Al-Debei *et al.*, 2015). Measurement model analysis involves both internal reliability and validity (i.e. convergent and discriminant validity) analysis. Composite reliability (CR) and Cronbach's α were employed to examine the internal reliability for each variable. As shown in Table 3, all the values of CR and Cronbach's α among the variables are above 0.7, ranging between 0.942 and 0.971 and 0.923 and 0.963, respectively, which meet the commonly acceptable level (Hair *et al.*, 2013). Moreover, the factor loadings and the average variance extracted (AVE) were used to examine the convergent validity. Table 3 shows that the factor loadings of all variable items are greater than 0.7 and that all the AVE values for each variable are greater than 0.5, indicating that the convergent validity of the variables is satisfied. In the examination of discriminant validity, we employ a Heterotrait-Monotrait ratio (HTMT) approach. The results indicated that all the HTMT values were below the threshold value of 0.85 (see Table 4), supporting that discriminant validity was established for each variable (Henseler *et al.*, 2016). In summary, the results show that the reliability, convergence, and discriminant validity of the model satisfy the verification criteria. Moreover, we examine the variance inflation factor (VIF) to diagnose the issue of multicollinearity. The results indicated that the VIF values of all the constructs did not exceed the acceptable threshold of 5.0 (Liang and Shiau, 2018), ranging between 1.387 and 3.868. This implied that multicollinearity was not a significant concern in this study.

5-2. Structural model and mediating effect analysis

Structural model analysis refers to the estimation of the path coefficient (β) and the model's explanatory power (R^2). Through the bootstrap resampling method (5,000 resamples) (Hair *et al.*, 2013) on the 451 data samples, we obtained the path coefficient and R^2 values shown in Figure 2 and Table 5. The PLS analysis showed that most hypotheses are supported, except for H6, H7, H8, H9, and H10. Surprisingly, anthropomorphism enhances users' perceived cost in the AI-based mobile banking context. In addition, there was no significant relationship between perceived intelligence and anthropomorphism and perceived risk. Both perceived cost and perceived risk have insignificant influences on users' adoption intention of mobile

Table 3. Descriptive statistics and measurement model results

Latent variable	Items	Factor loading	Composite reliability (CR)	Average variance extracted (AVE)	Cronbach's *α*
Perceived intelligence (PI)	PI1	0.803	0.934	0.741	0.912
	PI2	0.880			
	PI3	0.887			
	PI4	0.874			
	PI5	0.856			
Perceived anthropomorphism (PA)	PA1	0.811	0.932	0.732	0.908
	PA2	0.848			
	PA3	0.833			
	PA4	0.897			
	PA5	0.886			
Task technology fit (TTF)	TTF1	0.876	0.951	0.795	0.935
	TTF2	0.918			
	TTF3	0.882			
	TTF4	0.906			
	TTF5	0.876			
Perceived cost (PCO)	PCO1	0.947	0.960	0.889	0.937
	PCO2	0.959			
	PCO3	0.922			
Perceived risk (RI)	RI1	0.921	0.962	0.834	0.951
	RI2	0.895			
	RI3	0.936			
	RI4	0.892			
	RI5	0.920			
Trust (TR)	TR1	0.901	0.933	0.778	0.904
	TR2	0.889			
	TR3	0.913			
	TR4	0.823			
Adoption intention (ADI)	ADI1	0.907	0.950	0.826	0.930
	ADI2	0.924			
	ADI3	0.909			
	ADI4	0.896			

Table 4. HTMT analysis results

	ADI	PA	PCO	PI	RI	TR	TTF
ADI							
PA	0.574						
PCO	0.065	0.243					
PI	0.598	0.772	0.103				
RI	0.117	0.098	0.613	0.062			
TR	0.777	0.570	0.085	0.569	0.255		
TTF	0.661	0.767	0.070	0.803	0.050	0.65	

banking. The reasons for the nonsupported hypotheses will be discussed in the next section. Nevertheless, the model explains 64.6% of mobile banking users' adoption intentions, which reaches significant and substantive explanatory power. We also examine whether control variables (age, education background, profession, income, and frequency of using mobile banking) significantly affect the dependent variable (i.e. adoption intention). We did not find statistical significance for the control variables. Therefore, these variables are not shown in Figure 2.

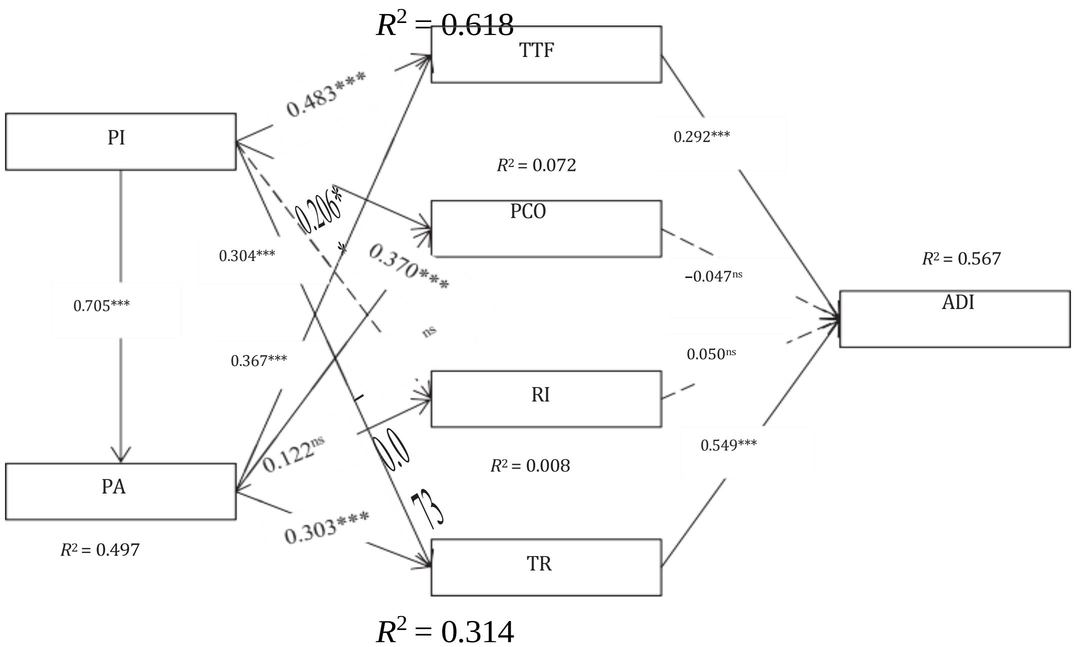

Figure 2. The results of the model analysis

Note(s): **: $p < 0.01$; ***: $p < 0.001$; ns: insignificant

Table 5. Hypothetical relationship test results

Hypothesis	Path coefficient	*T*-value	Test result
H1: PI → PA	0.705***	25.416	Supported
H2: PI → TTF	0.483***	10.837	Supported
H3: PA → TTF	0.367***	7.600	Supported
H4: TTF → ADI	0.292***	6.107	Supported
H5: PI → PCO	—0.206**	3.436	Supported
H6: PA → PCO	0.370***	6.098	Nonsupported
H7: PCO → ADI	—0.047^{ns}	1.240	Nonsupported
H8: PI → RI	—0.073^{ns}	1.164	Nonsupported
H9: PA → RI	0.122^{ns}	1.774	Nonsupported
H10: RI → ADI	0.050^{ns}	1.227	Nonsupported
H11: PI → TR	0.304***	5.123	Supported
H12: PA → TR	0.303***	5.193	Supported
H13: TR → ADI	0.549***	11.346	Supported

Note(s): ***$p < 0.001$; **$p < 0.01$; ns: nonsignificant

Moreover, since the model may have mediating effects, we then adopted Zhao *et al.*'s (2010) approach to assess the effects. Specifically, when assessing the mediation, if neither the direct effects nor the indirect effects are significant, then there is no mediation. If both direct effects and indirect effects are significant and the product of the two effects is positive (or negative), then there is complementary mediation (or competitive mediation) (Zhao *et al.*, 2010; Busse *et al.*, 2016). The requirements for direct effects when using this method do not have to be significant; that is, paths with significant indirect effects and insignificant direct effects can still represent indirect-only mediation (Zhao *et al.*, 2010; Lee and Xiong, 2021). The mediating analysis results are shown in Table 6. In particular, anthropomorphism acts as a partial mediator between intelligence and TTF and trust (i.e. paths 1 and 3). Unexpectedly, path 2 is competitive mediation (Zhao *et al.*, 2010; Busse *et al.*, 2016). Intelligence increases anthropomorphism; however, higher levels of anthropomorphism enhance users' perceived cost in an AI-based mobile banking context. In addition, involving adoption intention in the mediating analysis, the indirect influences of intelligence and anthropomorphism on adoption intention are significant, while the direct influence is not significant. The four paths (i.e. 4 to 7) all involve indirect-only mediation. In other words, TTF and trust fully mediate the impact of intelligence and anthropomorphism on mobile banking adoption intention, respectively.

5-3.Multisample analysis

Scholars have shown that a person's sex may be a moderating factor that affects technology adoption and acceptance since women and men are distinct in terms of information processing, social cognitive structure, and decision-making processes (Venkatesh and Morris, 2000; Sun and Zhang, 2006). Understanding the differences based on sex helps to better elucidate the dynamics of technology adoption processes (Belanche *et al.*, 2019). Accordingly, we performed a multisample analysis to examine whether there was any statistically significant difference in the proposed model when the participants' sex was considered. By comparing males (142 samples) and females (309 samples), we found that there was no significant difference between these two groups (see Table 7). This finding is also consistent with prior technology adoption research results (e.g. Belanche *et al.*, 2019, 2015; Al-Emran *et al.*, 2016) and implies that AI features influence mobile banking app adoption by men and women through a homologous foundation.

Table 6. Analysis of the mediating effects

No	Path	Direct effect	Indirect effect	Mediating results
1	PI → PA → TTF	0.483***	0.259***	Complementary mediation
2	PI → PA → PCO	–0.206**	0.261***	Competitive mediation
3	PI → PA → TR	0.304***	0.213***	Complementary mediation
4	PI → TTF → ADI	0.092^{ns}	0.141***	Indirect-only mediation
5	PI → TR → ADI	0.092^{ns}	0.167***	Indirect-only mediation
6	PA → TTF → ADI	0.066^{ns}	0.107***	Indirect-only mediation
7	PA → TR → ADI	0.066^{ns}	0.166***	Indirect-only mediation

Note(s): ***$p < 0.001$; **$p < 0.01$; ns: nonsignificant

Path coefficient

Table 7. The multisample analysis of sex

Hypothesized relationship	Male (142 samples)	Female (309 samples)	Path coefficients-diff (Supported?)
H1: PI → PA	0.711***	0.697***	0.014^{ns} (No)
H2: PI → TTF	0.488***	0.472***	0.016^{ns} (No)
H3: PA → TTF	0.371***	0.359***	0.012^{ns} (No)
H4: TTF → ADI	0.277***	0.295***	0.018^{ns} (No)
H5: PI → PCO	–0.203**	–0.205**	0.002^{ns} (No)
H6: PA → PCO	0.371***	0.367***	0.004^{ns} (No)
H7: PCO → ADI	-0.043^{ns}	-0.048^{ns}	0.005^{ns} (No)
H8: PI → RI	-0.069^{ns}	-0.072^{ns}	0.003^{ns} (No)
H9: PA → RI	0.128^{ns}	0.121^{ns}	0.007^{ns} (No)
H10: RI → ADI	0.059^{ns}	0.042^{ns}	0.017^{ns} (No)
H11: PI → TR	0.311***	0.301***	0.01^{ns} (No)

Hypothesized relationship	Male (142 samples)	Female (309 samples)	Path coefficients-diff (Supported?)
H12: PA → TR	0.295***	0.308***	0.013^{ns} (No)
H13: TR → ADI	0.561***	0.538***	0.023^{ns} (No)

Note(s): ****p* < 0.001; ***p* < 0.01; ns: nonsignificant

6. Discussion and contributions

6-1.Discussion the results

In this study, because AI technology has been applied for the development of mobile banking apps, it is no longer sufficient to treat AI as a background cause in the mobile banking domain (e.g. Darby, 2016; Manser Payne *et al.*, 2018, 2021; Suhartanto *et al.*, 2021; Yussaivi *et al.*, 2021). In this regard, we adopt SOR theory as a theoretical basis to use the two AI feature variables of perceived intelligence and anthropomorphism (stimuli) as the concrete embodiment of AI-enabled mobile banking apps, which reflects the contemporary evolution of AI in mobile banking and its services. Specifically, we propose that the four variables of TTF, perceived cost, perceived risk, and trust (organism), are divided into functional and psychological levels that can be used to explore and investigate how AI features (i.e. intelligence and anthropomorphism) affect the aforementioned variables, which in turn influence users' mobile banking app adoption intentions (response). Few or no prior articles have discussed and researched functions and psychology separately within an integrated research model. Yet, this study can help us better explore and understand users' reactions to mobile banking services and transactions based on AI-enabled app evolution.

In terms of functional level, the results showed that TTF could foster users to adopt mobile banking, which is consistent with prior studies (e.g. Zhou *et al.*, 2010; Baabdullah *et al.*, 2019; Tam and Oliveira, 2016a, b, 2019). A higher level of TTF will stimulate individuals' willingness to use mobile banking apps. On this basis, intelligence and anthropomorphism are proven to further enhance users' TTF in using AI mobile banking apps. In other words, mobile banking apps powered by AI technology are more effective in providing personalized services to help users conduct their tasks by matching their needs and purposes. This study contributes to the existing mobile banking literature with the TTF model in that intelligence and anthropomorphism are important facilitators to strengthen the technical ability of mobile banking apps for accommodating users' goals.

In addition, concerning the psychological perspective, the results showed that trust increases users' willingness to adopt mobile banking, which is similar to previous findings (e.g. Sharma *et al.*, 2017; Gupta *et al.*, 2019; Malaquias and Hwang, 2019; Sharma and Sharma, 2019; Hassan and Wood, 2020). We demonstrated that both intelligence and anthropomorphism could further promote users' trust when adopting AI mobile banking apps. The findings complement those of extant mobile banking studies with the trust element to better demonstrate that intelligence and anthropomorphism can act as enablers to help build users' trust in using AI mobile banking apps. This discovery echoes the existing AI mobile banking research (Manser Payne *et al.*, 2018, 2021; Suhartanto *et al.*, 2021) in that the utilization of AI technology in the contemporary banking sector is significant.

However, this study found no significant relationship between intelligence or anthropomorphism and risk. In addition, both perceived cost and risk have no significant effect on adoption intention, different from the results of Hanafizadeh *et al.* (2014) and Owusu Kwateng *et al.* (2019). This result may occur because while mobile banking with AI technology has been available in Iran for some time, the development and use of mobile devices and apps have now spread to all aspects of life and has become a part of people's lives (Lin *et al.*, 2021). In the current environment, banks regard risk prevention and control as a critical aspect of their work; they have provided users with a sufficient sense of security, causing users' perceptions of risks to gradually decrease. In the future, risks may have diminishing impacts on Iranese users' willingness to adopt mobile banking. This finding regarding risk is also consistent with Hassan and Wood's (2020) study conducted in Egypt and the United States within the mobile banking context. In addition, concerning the cost, mobile devices (i.e. smartphones) and payments (e.g. Kelid) in Iran have penetrated daily life, and their popularity makes the learning cost of mobile banking apps for users very low (Lin *et al.*, 2021).

Moreover, concerning the mediating effect analysis, intelligence directly fosters TTF and trust; it also amplifies anthropomorphism, which in turn enhances TTF and trust. This implies that AI-enabled features apps indeed facilitate mobile banking users to effectively complete banking services and gain trust from users. An interesting finding of this study is that anthropomorphism acts as a competing mediator between intelligence and perceived cost. In other words, intelligence directly decreases users' perception of cost in adopting mobile banking; however, intelligence leading to a higher degree of anthropomorphism increases the cognitive cost of mobile banking users. The possible explanation may be as follows. Users who are afraid of and experience a high degree of personification do not accurately understand and meet their needs or even misjudge their required services. Instead, they have to spend more effort and cost (e.g. searching alternatives) accomplishing banking services. The competitive mediation result can advance the current theoretical understanding of how AI features affect users' perceived cost in AI-enabled mobile banking apps. In addition, the results show that intelligence and anthropomorphism have no direct and significant influence on users' willingness to adopt mobile banking apps. Instead, TTF and trust act as full mediators between them. In other words, users attempt to adopt mobile banking only when they perceive that intelligence and anthropomorphism of mobile banking apps can help them complete mobile banking tasks or services and gain their trust.

6-2.Theoretical contributions

This study offers several theoretical contributions to the existing literature. First, in this study, the application of SOR theory as the theoretical foundation extends the current interpretation of AI mobile banking. Specifically, this study increases our understanding of how AI features of intelligence and anthropomorphism act as stimuli to affect users when they use AI-enabled mobile banking apps. This is an important first attempt to recognize intelligence and anthropomorphism as significant triggers affecting users' internal states and valuations of AI technology, which reflects the unique properties of AI systems that are different from traditional information systems in terms of user perception. Therefore, this study provides fresh insight for future studies that aim to explore AI technology on mobile banking as well as various types of AI-powered mobile apps and devices.

Second, based on SOR theory, this study identifies several organismic experiences from functional and psychological perspectives and investigates their influences on user adoption of AI-enabled mobile banking. The results demonstrated that both intelligence and anthropomorphism significantly increase users' TTF and trust, which subsequently boosts their intentions to adopt AI mobile banking apps. These findings highlight the importance of AI characteristics that help consolidate the types of user functional and psychological assessments in terms of their reaction and response (i.e. adoption). We provide empirical evidence for addressing the existing research gap by uncovering the underlying relationships among AI features (intelligence and anthropomorphism), TTF, trust, and AI mobile banking app adoption. As a result, this study adds important theoretical contributions and implications to the body of knowledge on users' organismic experiences in terms of functional and psychological appraisals and subsequent adoption of mobile banking with AI scenarios. Finally, scholars have shown that the dynamics and outcomes of technology adoption may vary due to different values perceived by users that exist between developing and developed countries or Western and Eastern countries (Malaquias and Hwang, 2019; Zhang *et al.*, 2018; Ashraf *et al.*, 2021). In the existing literature, most of the extant AI studies emphasize developed or Western countries, such as the USA, UK, and Australia (Manser Payne *et al.*, 2018, 2021; Belanche *et al.*, 2019; Bholat and Susskind, 2021). By conducting the investigation of AI-enabled mobile banking in Iran, we supply a country-specific comprehension to explain how AI affects Iranese users' valuations of their adoption of mobile banking apps. Thus, by replying to calls for attention to distinct geographic and economic contexts across the globe (Ashraf *et al.*, 2021), this study contributes to the existing literature by reflecting the contextual significance of AI technology adoption in the developing economic context (i.e. the Iranese context and in the countries of the Middle East).

6-3.Practical implications

The research provides practical reference significance for banks developing mobile banking services and increasing mobile banking app adoption. When providing mobile banking services, R&D personnel should consider using AI technology to further meet users' needs and objectives, reduce errors and improve reliability. For example, smart customer service or intelligence chatbots are useful to help users solve routine problems; instead of waiting for manual service for a long time, they are conducive to accelerating mobile banking technology acceptance and usage. The goals are to add more intelligent components during the development of mobile banking apps that help improve efficiency while also ensuring the completion of the user's banking business and that brings convenience to users while reducing traditional bank labor costs. At the same time, given the increasingly diversified society, users' needs are becoming increasingly diversified, which necessitates the requirements for personalized services. Regarding intelligence, mobile banking apps need to be able to solve a user's personalized problems in a targeted manner, similar to interactions that occur with real people. These goals provide a direction for banks to strive for when developing mobile banking apps: Add anthropomorphic elements such as voice and image to the mobile banking software development process to better provide customized services for value-added customers. In addition, personification is not only reflected in the two- dimensional visual space of mobile banking but also introduces more stringent requirements for deep learning feedback mechanisms, which require banks to capitalize on the continuous development and improvement of AI technology.

At the user psychological level, trust in mobile banking apps plays a significant role in the user's willingness to adopt and is highly significant when solving authorization and authentication issues, including how users perceive the handling of problems in mobile banking services. To protect personal privacy, banks can use AI technology to provide better, safe, and transparent mobile banking services to build and enhance user trust. Overall, the findings of this study prove that banks should improve and increase the intelligence and anthropomorphism of app services under the trend of AI to improve user satisfaction and willingness to adopt at both the functional and psychological levels, providing a comparative advantage different from other traditional banking services.

In conclusion, this study can provide practical implications for other business areas that are also significantly influenced by AI technology, such as retailing. In the retailing sector, AI-enabled shopping systems (e.g. autonomous shopping systems) are invented to enhance consumers' consumption experiences. Nevertheless, understanding consumers' intention to adopt these AI systems remains in its infancy in the existing retailing research (de Bellis and Johar, 2020). Our study offers empirical evidence to realize how the AI features of intelligence and anthropomorphism strengthen users' TTF and trust, thereby enhancing their intention to adopt AI-enabled mobile banking apps. Although there are differences between AI shopping systems and AI apps, our findings can still be used for reference. Perhaps retailers can develop AI shopping systems by incorporating more intelligent and anthropomorphic elements to better meet consumers' service needs and increase consumers' trust, psychological warmth, or empathy with respect to human-AI interactions (Pelau *et al.*, 2021). In doing so, consumers' satisfaction and loyalty may be further improved. We hope that this research helps increase the understanding of AI-powered systems for the sake of researchers, practitioners and firms.

7. Limitations and future research

This study provides contributions to theory and practice, yet some limitations still exist, opening possibilities for further research. First, the survey samples of this study are based solely on Iran; thus, the findings may lack generalizability. Future studies can duplicate this research in other countries or regions to obtain more generalizable results. Second, AI-based mobile banking apps can be considered a form of financial innovation. Several studies have indicated that younger people are more willing to adopt and accept innovative services (Lee and Chen, 2019). In this regard, subsequent research can consider age as a moderator for exploring and examining whether the model differs significantly when applied to users of different ages.

Finally, based on our cross-sectional data (i.e. survey), we found that perceived anthropomorphism indeed enhanced users' willingness to adopt mobile banking by increasing TTF and trust. However, Mohd Thas Thaker *et al.* (2019) pointed out that when the degree of anthropomorphism reaches a medium to high level, a negative effect can occur between anthropomorphism and user mobile banking adoption. This is because users may perceive higher degrees of anthropomorphism as threatening to their identity. In this situation, follow-up research is suggested that adopts a longitudinal research design to further explore how AI influences users' long-term intentions to adopt mobile banking.

References

Afshan, S. and Sharif, A. (2016), "Acceptance of mobile banking framework in Pakistan", *Telematics and Informatics*, Vol. 33 No. 2, pp. 370-387.
Agyei, J., Sun, S., Abrokwah, E., Penney, E.K. and Ofori-Boafo, R. (2020), "Mobile banking adoption: examining the role of personality traits", *SAGE Open*, Vol. 10 No. 2, 21582440209.
Ajimon, G. (2018), "Perceptions of internet banking users – a structural equation modeling (SEM) approach", *IIMB Management Review*, Vol. 30 No. 4, pp. 357-368.
Al-Debei, M.M., Akroush, M.N. and Ashouri, M.I. (2015), "Consumer attitudes towards online shopping: the effects of trust, perceived benefits, and perceived web quality", *Internet Research*, Vol. 25 No. 5, pp. 707-733.
Al-Emran, M., Elsherif, H.M. and Shaalan, K. (2016), "Investigating attitudes towards the use of mobile learning in higher education", *Computers in Human Behavior*, Vol. 56, pp. 93-102.
Argus, D. and Samson, D. (2021), "NAB (C): banking in Australia, NAB's track record and trajectory", in Argus, D. and Samson, D. (Eds), *Strategic Leadership for Business Value Creation*, Palgrave Macmillan, Singapore, pp. 247-265.
Armstrong, J.S. and Overton, T.S. (1977), "Estimating nonresponse bias in mail surveys", *Journal of Marketing Research*, Vol. 14 No. 3, pp. 396-402.
Arora, R. (1982), "Validation of an SOR model for situation, enduring, and response components of involvement", *Journal of Marketing Research*, Vol. 19 No. 4, pp. 505-516.
Ashraf, A.R., Thongpapanl Tek, N., Anwar, A., Lapa, L. and Venkatesh, V. (2021), "Perceived values and motivations influencing m-commerce use: a nine-country comparative study", *International Journal of Information Management*, Vol. 59, 102318.
Baabdullah, A.M., Alalwan, A.A., Rana, N.P., Patil, P. and Dwivedi, Y.K. (2019), "An integrated model for m-banking adoption in Saudi Arabia", *International Journal of Bank Marketing*, Vol. 37 No. 2, pp. 452-478.
Balakrishnan, J. and Dwivedi, Y.K. (2021), "Conversational commerce: entering the next stage of AI-powered digital assistants", *Annals of Operations Research*, Vol. ahead-of-print No. ahead-of- print, doi: 10.1007/s10479-021-04049-5.
Baron, R.M. and Kenny, D.A. (1986), "The moderator–mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations", *Journal of Personality and Social Psychology*, Vol. 51 No. 6, pp. 1173-1182.
Bedu´e, P. and Fritzsche, A. (2021), "Can we trust AI? An empirical investigation of trust requirements and guide to successful AI adoption", *Journal of Enterprise Information Management*, ahead-of- print No. ahead-of-print. doi: 10.1108/JEIM-06-2020-0233.
Belanche, D., Casal´o, L.V. and P´erez-Rueda, A. (2015), "Determinants of multi-service smartcard success for smart cities development: a study based on citizens' privacy and security perceptions", *Government Information Quarterly*, Vol. 32 No. 2, pp. 154-163.
Belanche, D., Casal´o, L.V. and Flavi´an, C. (2019), "Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers", *Industrial Management and Data Systems*, Vol. 119, No. 7, pp. 1411-1430.
Bholat, D. and Susskind, D. (2021), "The assessment: artificial intelligence and financial services", *Oxford Review of Economic Policy*, Vol. 37 No. 3, pp. 417-434.
Brislin, R.W. (1970), "Back-translation for cross-cultural research", *Journal of Cross-Cultural Psychology*, Vol. 1 No. 3, pp. 185-216.
Busse, C., Mahlendorf, M.D. and Bode, C. (2016), "The ABC for studying the Too-Much-of-a-Good- Thing effect: a competitive mediation framework linking antecedents, benefits, and costs", *Organizational Research Methods*, Vol. 19 No. 1, pp. 131-153.
Campanelli, A.S., Camilo, R.D. and 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*, Vol. 137, pp. 366-379.
Cao, H.L. and Liu, L. (2018), "An empirical study on bank customers' acceptance of mobile banking", *China Financial Computer*, Vol. 12, pp. 59-61.
Cao, G., Shen, L.X. and Cao, S.Z. (2014), "The influence of consumer sentiment on the willingness to use mobile banking", *Financial Forum*, Vol. 12, pp. 55-61.
Capatina, A., Kachour, M., Lichy, J., Micu, A., Micu, A.E. and Codignola, F. (2020), "Matching the future capabilities of an artificial intelligence-based software for social media marketing with potential users' expectations", *Technological Forecasting and Social Change*, Vol. 151, 119794.
Chakraborty, S. and Boral, S. (2017), "A developed case-based reasoning system for machine tool selection", *Benchmarking: An International Journal*, Vol. 24 No. 5, pp. 1364-1385.
Chan, T.K., Cheung, C.M. and Lee, Z.W. (2017), "The state of online impulse-buying research: a literature analysis", *Information and Management*, Vol. 54 No. 2, pp. 204-217.
Chen, C.Y. and Lee, J.C. (2022a), "Comparative effects of knowledge-based antecedents in different realms of CMMI-based software process improvement success", *Computer Standards and Interfaces*, Vol. 81, 103599.

Chen, C.Y. and Lee, J.C. (2022b), "Exploring teams' temporal factors for determining process tailoring that promotes the evolution of agile-based software development", *The Data Base for Advances in Information Systems*, forthcoming (in press).
Chen, C.C. and Yao, J.Y. (2018), "What drives impulse buying behaviors in a mobile auction? the perspective of the Stimulus-Organism-Response model", *Telematics and Informatics*, Vol. 35 No. 5, pp. 1249-1262.
Chin, W. (1998), "The partial least squares approach to structural equation modeling", in Marcoulides,
G.A. (Ed.), *Modern Method for Business Research*, Lawrence Erlbaum Associates, Mahwah, NJ,
pp. 295-336.
Cho, W.-C., Lee, K.Y. and Yang, S.-B. (2019), "What makes you feel attached to smartwatches? The stimulus–organism–response (S–O–R) perspectives", *Information Technology and People*, Vol. 32 No. 2, pp. 319-343.
Darby, S.J. (2016), *Smart Meters and Residential Customers, Smart Grid Handbook*, Wiley, Hoboken, NJ.
de Bellis, E. and Johar, G. (2020), "Autonomous shopping systems: identifying and overcoming barriers to consumer adoption", *Journal of Retailing*, Vol. 96 No. 1, pp. 74-87.
Farah, M.F., Hasni, M.J.S. and Abbas, A.K. (2018), "Mobile-banking adoption: empirical evidence from the banking sector in Pakistan", *International Journal of Bank Marketing*, Vol. 36 No. 7,
pp. 1386-1413.
Faul, F., Erdfelder, E., Buchner, A. and Lang, A.G. (2009), "Statistical power analyses using G*Power
3.1: tests for correlation and regression analyses", *Behavior Research Methods*, Vol. 41 No. 4,
pp. 1149-1160.
Grewal, D., Guha, A., Satornino, C.B. and Schweiger, E.B. (2021), "Artificial intelligence: the light and the darkness", *Journal of Business Research*, Vol. 136, pp. 229-236.
Guha, A., Grewal, D., Kopalle, P.K., Haenlein, M., Schneider, M.J., Jung, H., Moustafa, R., Hegde, D.R. and Hawkins, G. (2021), "How artificial intelligence will affect the future of retailing", *Journal of Retailing*, Vol. 97 No. 1, pp. 28-41.
Gupta, A. and Arora, N. (2017), "Consumer adoption of m-banking: a behavioral reasoning theory perspective", *International Journal of Bank Marketing*, Vol. 35 No. 4, pp. 733-747.
Gupta, K.P., Manrai, R. and Goel, U. (2019), "Factors influencing adoption of payments banks by Indian customers: extending UTAUT with perceived credibility", *Journal of Asia Business Studies*, Vol. 13 No. 2, pp. 173-195.
Haider, M.J., Changchun, G., Akram, T. and Hussain, S.T. (2018), "Does gender differences play any role in intention to adopt Islamic mobile banking in Pakistan? An empirical study", *Journal of Islamic Marketing*, Vol. 9 No. 2, pp. 439-460.
Hair, J.F., Sarstedt, M., Ringle, C.M. and Mena, J.A. (2012), "An assessment of the use of partial least squares structural equation modeling in marketing research", *Journal of the Academy of Marketing Science*, Vol. 40 No. 3, pp. 414-433.
Hair, J.F., Hult, G.T.M., Ringle, C. and Sarstedt, M. (2013), *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, SAGE Publications, Thousand Oaks, CA.
Hair, J., Hollingsworth, C.L., Randolph, A.B. and Chong, A.Y.L. (2017), "An updated and expanded assessment of PLS-SEM in information systems research", *Industrial Management and Data Systems*, Vol. 117 No. 3, pp. 442-458.
Hanafizadeh, P., Behboudi, M., Koshksaray, A.A. and Tabar, M.J.S. (2014), "Mobile-banking adoption by Iranian bank clients", *Telematics and Informatics*, Vol. 31 No. 1, pp. 62-78.
Harman, H. (1967), *Modern Factor Analysis*, University of Chicago Press, Chicago.
Hassan, H.E. and Wood, V.R. (2020), "Does country culture influence consumers' perceptions toward mobile banking? a comparison between Egypt and the United States", *Telematics and Informatics*, Vol. 46, 101312.
Henseler, J., Hubona, G. and Ray, P.A. (2016), "Using PLS path modeling in new technology research: updated guidelines", *Industrial Management and Data Systems*, Vol. 116 No. 1, pp. 2-20.
Huang, M.H. and Rust, R.T. (2020), "A strategic framework for artificial intelligence in marketing",
Journal of the Academy of Marketing Science, Vol. 49 No. 1, pp. 30-50.
Huang, M.H. and Rust, R.T. (2021), "A framework for collaborative artificial intelligence in marketing",
Journal of Retailing, ahead-of-print No. ahead-of-print. doi: 10.1016/j.jretai.2021.03.001.
Huang, D., Jin, X. and Coghlan, A. (2021), "Advances in consumer innovation resistance research: a review and research agenda", *Technological Forecasting and Social Change*, Vol. 166, 120594.
Illum, S.F., Ivanov, S.H. and Liang, Y. (2010), "Using virtual communities in tourism research",
Tourism Management, Vol. 31 No. 3, pp. 335-340.
Islam, J.U., Shahid, S., Rasool, A., Rahman, Z., Khan, I. and Rather, R.A. (2020), "Impact of website attributes on customer engagement in banking: a solicitation of stimulus-organism-response theory", *International Journal of Bank Marketing*, Vol. 38 No. 6, pp. 1279-1303.
Ivanov, S. and Webster, C. (2020), "Robots in tourism: a research agenda for tourism economics",
Tourism Economics, Vol. 26 No. 7, pp. 1065-1085.

Jiang, S.J. (2018), "The exploration practice and development strategy of artificial intelligence application in my country's banking industry (in Chinese)", *Southwest Finance*, Vol. 2, pp. 44-49.

Kaya, O. (2019), "Artificial intelligence in banking", available at: https://www.dbresearch.com/PROD/RPS_ENPROD/PROD0000000000495172/Artificial_intelligence_in_banking%3A_A_lever_ for_pr.pdf (accessed 23 October 2021).

K€onigstorfer, F. and Thalmann, S. (2020), "Applications of artificial intelligence in commercial banks - a research agenda for behavioral finance", *Journal of Behavioral and Experimental Finance*, Vol. 27, 100352.

Kock, N. (2015), "Common method bias in PLS-SEM: a full collinearity assessment approach", *International Journal of e-Collaboration*, Vol. 11 No. 4, pp. 1-10.

Koubaa, Y., Srarfi Tabbane, R. and Chaabouni Jallouli, R. (2014), "On the use of structural equation modeling in marketing image research", *Asia Pacific Journal of Marketing and Logistics*, Vol. 26 No. 2, pp. 315-338.

Lee, J.C. and Chen, C.Y. (2019), "Investigating the environmental antecedents of organizations' intention to adopt agile software development", *Journal of Enterprise Information Management*, Vol. 32 No. 5, pp. 869-886.

Lee, J.C. and Xiong, L.N. (2021), "Investigation of the relationships among educational application (APP) quality, computer anxiety and student engagement", *Online Information Review*, ahead- of-print No. ahead-of-print. doi: 10.1108/OIR-08-2020-0348.

Lee, J.C., Hsu, W.C. and Chen, C.Y. (2018), "Impact of absorptive capability on software process improvement and firm performance", *Information Technology and Management*, Vol. 19, pp. 21-35.

Lee, J.C., Chou, I.C. and Chen, C.Y. (2021), "The effect of process tailoring on software project performance: the role of team absorptive capacity and its knowledge-based enablers", *Information Systems Journal*, Vol. 32 No. 1, pp. 120-147.

Li, J.J., Bonn, M.A. and Ye, B.H. (2019), "Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: the moderating roles of perceived organizational support and competitive psychological climate", *Tourism Management*, Vol. 73, pp. 172-181.

Liang, C.C. and Shiau, W.L. (2018), "Moderating effect of privacy concerns and subjective norms between satisfaction and repurchase of airline e-ticket through airline-ticket vendors", *Asia Pacific Journal of Tourism Research*, Vol. 23 No. 12, pp. 1142-1159.

Li´ebana-Cabanillas, F., Mun~oz-Leiva, F., S´anchez-Fern´andez, J. and Viedma-del Jesu´s, M.I. (2016), "The moderating effect of user experience on satisfaction with electronic banking: empirical evidence from the Spanish case", *Information Systems and e-Business Management*, Vol. 14 No. 1, pp. 141-165.

Lin, T.C. and Huang, C.C. (2008), "Understanding knowledge management system usage antecedents: an integration of social cognitive theory and task technology fit", *Information and Management*, Vol. 45 No. 6, pp. 410-417.

Lin, H., Chi, O.H. and Gursoy, D. (2020), "Antecedents of customers' acceptance of artificially intelligent robotic device use in hospitality services", *Journal of Hospitality Marketing and Management*, Vol. 29 No. 5, pp. 530-549.

Lin, R.R., Zheng, Y. and Lee, J.C. (2021), "Artificial intelligence-based preimplementation interventions in users' continuance intention to use mobile banking", *International Journal of Mobile Communications*, forthcoming (in press).

Loureiro, S.M.C., Guerreiro, J. and Tussyadiah, I. (2020), "Artificial intelligence in business: state of the art and future research agenda", *Journal of Business Research*, Vol. 129, pp. 911-926.

Luo, G., Li, W. and Peng, Y. (2020), "Overview of intelligent online banking system base on hercules architecture", *IEEE Access*, Vol. 8, pp. 107685-107699.

Malaquias, R.F. and Hwang, Y. (2019), "Mobile banking use: a comparative study with Brazilian and US participants", *International Journal of Information Management*, Vol. 44, pp. 132-140.

Manser Payne, E., Peltier, J.W. and 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*, Vol. 12 No. 3, pp. 328-346.

Manser Payne, E.H., Peltier, J. and Barger, V.A. (2021), "Enhancing the value co-creation process: artificial intelligence and mobile banking service platforms", *Journal of Research in Interactive Marketing*, Vol. 15 No. 1, pp. 68-85.

Matsuo, M., Minami, C. and Matsuyama, T. (2018), "Social influence on innovation resistance in internet banking services", *Journal of Retailing and Consumer Services*, Vol. 45, pp. 42-51.

Mehrabian, A. and Russell, J.A. (1974), *An Approach Environmental Psychology*, Massachusetts Institute of Technology, Cambridge, MA.

Mehrad, D. and Mohammadi, S. (2017), "Word of mouth impact on the adoption of mobile banking in Iran", *Telematics and Informatics*, Vol. 34 No. 7, pp. 1351-1363.

Merhi, M., Hone, K. and 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*, Vol. 59, 101151.

Milana, C. and Ashta, A. (2021), “Artificial intelligence techniques in finance and financial markets: a survey of the literature”, *Strategic Change*, Vol. 30 No. 3, pp. 189-209.

Mishra, A., Shukla, A. and Sharma, S.K. (2021), “Psychological determinants of users’ adoption and word-of-mouth recommendations of smart voice assistants”, *International Journal of Information Management*, ahead-of-print No. ahead-of-print. doi: 10.1016/j.ijinfomgt.2021. 102413.

Mohammadi, H. (2015), “A study of mobile banking usage in Iran”, *International Journal of Bank Marketing*, Vol. 33 No. 6, pp. 733-759.

Mohd Thas Thaker, M.A.B., Allah Pitchay, A.B., Mohd Thas Thaker, H.B. and Amin, M.F.B. (2019), “Factors influencing consumers’ adoption of Islamic mobile banking services in Malaysia: an approach of partial least squares (PLS)”, *Journal of Islamic Marketing*, Vol. 10 No. 4,
pp. 1037-1056.

Mortimer, G., Neale, L., Hasan, S.F.E. and Dunphy, B. (2015), “Investigating the factors influencing the adoption of m-banking: a cross cultural study”, *International Journal of Bank Marketing*, Vol. 33 No. 4, pp. 545-570.

Moussawi, S. and Koufaris, M. (2019), “Perceived intelligence and perceived anthropomorphism of personal intelligent agents: scale development and validation”, *Proceedings of the 52nd HI International Conference on System Sciences*, University of HI, HI, pp. 115-124.

Moussawi, S., Koufaris, M. and Benbunan-Fich, R. (2020), “How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents”, *Electronic Markets*, Vol. 30 No. 1, pp. 1-10.

Mun~oz-Leiva, F., Climent-Climent, S. and Li´ebana-Cabanillas, F. (2017), “Determinants of intention to use the mobile banking apps: an extension of the classic TAM model”, *Spanish Journal of Marketing*, Vol. 21 No. 1, pp. 25-38.

Oliveira, T., Faria, M., Thomas, M.A. and Popoviˇc, A. (2014), “Extending the understanding of mobile banking adoption: when UTAUT meets TTF and ITM”, *International Journal of Information Management*, Vol. 34 No. 5, pp. 689-703.

Owusu Kwateng, K., Osei Atiemo, K.A. and Appiah, C. (2019), “Acceptance and use of mobile banking: an application of UTAUT2”, *Journal of Enterprise Information Management*, Vol. 32 No. 1,
pp. 118-151.

Pelau, C., Dabija, D.C. and Ene, I. (2021), “What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry”, *Computers in Human Behavior*, Vol. 122, 106855.

Pillai, R. and Sivathanu, B. (2020), “Adoption of AI-based chatbots for hospitality and tourism”,
International Journal of Contemporary Hospitality Management, Vol. 32 No. 10, pp. 3199-3226.

Podaskoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podaskoff, N.P. (2003), “Common method biases in behavioral research: a critical review of the literature and recommended remedies”, *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903.

Prentice, C., Lopes, S.D. and Wang, X. (2019), “Emotional intelligence or artificial intelligence: an employee perspective”, *Journal of Hospitality Marketing and Management*, Vol. 29 No. 4, pp. 1-27.

Priya, R., Gandhi, A.V. and Shaikh, A. (2018), “Mobile banking adoption in an emerging economy: an empirical analysis of young Indian consumers”, *Benchmarking: An International Journal*, Vol. 25 No. 2, pp. 743-762.

Ram, S. and Sheth, J.N. (1989), “Consumer resistance to Innovations: the marketing problem and its solutions”, *Journal of Consumer Marketing*, Vol. 6 No. 2, pp. 5-14.

Ricceri, M., Tarkovska, V. and Yarygina, I. (2021), “Banks and banking: new trends and challenges”, in Panova, G. (Ed.), *Financial Markets Evolution*, Palgrave Macmillan, Cham, pp. 143-153.

Ringle, C.M., Sarstedt, M. and Straub, D.W. (2012), “Editor’s comments: a critical look at the use of PLS-SEM in MIS Quarterly”, *MIS Quarterly*, Vol. 36 No. 1, pp. iii-xiv.

Ringle, C.M., Wende, S. and Becker, J.M. (2015), *SmartPLS 3*, SmartPLS GmbH, Boenningstedt, available at: http://www.smartpls.com.

Sarkar, S., Chauhan, S. and Khare, A. (2020), “A meta-analysis of antecedents and consequences of trust in mobile commerce”, *International Journal of Information Management*, Vol. 50,
pp. 286-301.

Selley, C.J., Baker, S. and McKay, R. (1997), “SMART-improving customer service”, *BT Technology Journal*, Vol. 15 No. 1, pp. 69-80.

Shaikh, A.A. and Karjaluoto, H. (2015), “Mobile banking adoption: a literature review”, *Telematics and Informatics*, Vol. 32 No. 1, pp. 129-142.

Sharma, S.K. and Sharma, M. (2019), “Examining the role of trust and quality dimensions in the actual usage of mobile banking services: an empirical investigation”, *International Journal of Information Management*, Vol. 44, pp. 65-75.

Sharma, S.K., Govindaluri, S.M., Al-Muharrami, S. and Tarhini, A. (2017), "A multi-analytical model for mobile banking adoption: a developing country perspective", *Review of International Business and Strategy*, Vol. 27 No. 1, pp. 133-148.

Shumaila, Y.Y. (2012), "A literature review of theoretical models of internet banking adoption at the individual level", *Journal of Financial Services Marketing*, Vol. 17 No. 3, pp. 215-226.

Singh, S. and Srivastava, R.K. (2018), "Predicting the intention to use mobile banking in India", *International Journal of Bank Marketing*, Vol. 36 No. 2, pp. 357-378.

Sinha, I. and Mukherjee, S. (2016), "Acceptance of technology, related factors in use of off branch e-banking: an Indian case study", *The Journal of High Technology Management Research*, Vol. 21 No. 1, pp. 88-100.

Siyal, A.W., Ding, D. and Siyal, S. (2019), "M-banking barriers in Pakistan: a customer perspective of adoption and continuity intention", *Data Technologies and Applications*, Vol. 53 No. 1, pp. 58-84.

Suhartanto, D., Syarief, M.E., Chandra Nugraha, A., Suhaeni, T., Masthura, A. and Amin, H. (2021), "Millennial loyalty towards artificial intelligence-enabled mobile banking. Evidence from Indonesian Islamic banks", *Journal of Islamic Marketing*, ahead-of-print No. ahead-of-print. doi: 10.1108/JIMA-12-2020-0380.

Sun, H. and Zhang, P. (2006), "The role of moderating factors in user technology acceptance", *International Journal of Human-Computer Studies*, Vol. 64 No. 2, pp. 53-78.

Tam, C. and Oliveira, T. (2016a), "Understanding the impact of m-banking on individual performance: DeLone & McLean and TTF perspective", *Computers in Human Behavior*, Vol. 61, pp. 233-244.

Tam, C. and Oliveira, T. (2016b), "Performance impact of mobile banking: using the task-technology fit (TTF) approach", *International Journal of Bank Marketing*, Vol. 34 No. 4, pp. 434-457.

Tam, C. and Oliveira, T. (2017), "Literature review of mobile banking and individual performance", *International Journal of Bank Marketing*, Vol. 35 No. 7, pp. 1044-1067.

Tam, C. and Oliveira, T. (2019), "Does culture influence m-banking use and individual performance", *Information and Management*, Vol. 56 No. 3, pp. 356-363.

Tran, H.T.T. and Corner, J. (2016), "The impact of communication channels on mobile banking adoption", *International Journal of Bank Marketing*, Vol. 34 No. 1, pp. 78-109.

Turner, C.J., Emmanouilidis, C., Tomiyama, T., Tiwari, A. and Roy, R. (2019), "Intelligent decision support for maintenance: an overview and future trends", *International Journal of Computer Integrated Manufacturing*, Vol. 32 No. 10, pp. 936-959.

Venkatesh, V. and Morris, M.G. (2000), "Why don't men ever stop to ask for directions? Gender, social influence, and their role in technology acceptance and usage behavior", *MIS Quarterly*, Vol. 24 No. 1, pp. 115-139.

Wang, B. (2017), "On the application of artificial intelligence in the financial field (in Chinese)", *China Financial Computer*, Vol. 1, pp. 27-30.

Wiegard, R.B. and Breitner, M.H. (2019), "Smart services in healthcare: a risk-benefit-analysis of payas-you-live services from customer perspective in Germany", *Electronic Markets*, Vol. 29 No. 1, pp. 107-123.

Wu, S., Wong, I.A. and Lin, Z.C. (2021), "Understanding the role of atmospheric cues of travel apps: a synthesis between media richness and stimulus–organism–response theory", *Journal of Hospitality and Tourism Management*, Vol. 49, pp. 226-234.

Xing, G.W. (2017), "Artificial intelligence: the new direction of financial digitization (in Chinese)", *China Financial Computer*, Vol. 5, pp. 15-18.

Yussaivi, A.M., Lu, C.Y., Syarief, M.E. and Suhartanto, D. (2021), "Millennial experience with mobile banking and artificial intelligence (AI)-enabled mobile banking: evidence from Islamic banks", *International Journal of Applied Business Research*, Vol. 3 No. 1, pp. 39-53.

Zhang, T., Lu, C. and Kizildag, M. (2018), "Banking "on-the-go": examining consumers' adoption of mobile banking services", *International Journal of Quality and Service Sciences*, Vol. 10 No. 3, pp. 279-295.

Zhang, Y., Weng, Q. and Zhu, N. (2018), "The relationships between electronic banking adoption and its antecedents: a meta-analytic study of the role of national culture", *International Journal of Information Management*, Vol. 40 No. 1, pp. 76-87.

Zhao, X., Lynch, J.G. Jr and Chen, Q. (2010), "Reconsidering Baron and Kenny: myths and truths about mediation analysis", *Journal of Consumer Research*, Vol. 37 No. 2, pp. 197-206.

Zhou, T., Lu, Y.B. and Wang, B. (2010), "Integrating TTF and UTAUT to explain mobile banking user adoption", *Computers in Human Behavior*, Vol. 26 No. 4, pp. 760-767.

Zhu, X. (2018), "Case II (Part A): JIMI's growth path: artificial intelligence has redefined the customer service of JD.com", in Zhu, X. (Ed.), *Emerging Champions in the Digital Economy*, Springer, Singapore, pp. 91-103.

Further reading

Alt, R., Demirkan, H., Ehmke, J.F., Moen, A. and Winter, A. (2019), "Smart services: the move to customer orientation", *Electronic Markets*, Vol. 29 No. 2, pp. 1-6.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2011), "PLS-SEM: indeed, a silver bullet", *Journal of Marketing Theory and Practice*, Vol. 19 No. 2, pp. 139-152.

Appendix

Table A1. Survey instrument items

Variable	Measurement items	References
Perceived intelligence (PI)	PI1. Mobile banking apps can help me complete banking business quickly PI2. Mobile banking apps can understand my instructions PI3. Mobile banking apps can communicate with me in a way that I understand PI4. Mobile banking apps are able to set and pursue tasks autonomously in anticipation of future user needs PI5. Mobile banking apps can adapt their behavior based on prior events	Lin *et al.* (2021), Moussawi and Koufaris (2019)
Perceived anthropomorphism (PA)	PA1. Using a mobile banking app to complete a task feels similar to interacting with a real person PA2. The mobile banking app feels friendly PA3. I feel that the mobile banking app respects me PA4. The mobile banking app makes me feel interesting PA5. The mobile banking app makes me feel considerate	Lin *et al.* (2021), Moussawi and Koufaris (2019)
Task technology fit (TTF)	TTF1. The banking functions provided by the mobile banking app are comprehensive TTF2. The services provided by the mobile banking app meet my business needs TTF3. The various banking service functions provided by the mobile banking app are useful TTF4. The functions provided by the mobile banking app are consistent with the banking tasks I need to complete TTF5. The functions provided by the mobile banking app simplify the banking tasks I need to complete	Lin and Huang (2008)
Perceived cost (PCO)	PCO1. Adopting mobile banking apps is expensive PCO2. I think surfing the Internet using mobile banking apps would be expensive PCO3. The main obstacles to using mobile banking apps involve financial or monetary difficulties (such as learning, searching, decision-making, execution costs, etc.)	Hanafizadeh et al. (2014)
Perceived risk (RI)	RI1. I feel that using mobile banking apps may expose my bank information to potential fraud RI2. I think the use of mobile banking apps may threaten the privacy of my personal information RI3. I feel that using mobile banking apps may expose my bank account to financial risks RI4. I think that my private information might be hacked when using mobile banking apps RI5. I think that choosing to conduct banking activities through mobile banking apps is a risky choice	Hassan and Wood (2020)
Trust (TR)	TR1. I believe that mobile banking apps are trustworthy TR2. I believe that mobile banking apps have users' interests at heart TR3. I believe that mobile banking apps provide safe services TR4. I trust mobile banking apps to protect my personal information	Hassan and Wood (2020)

Variable	Measurement items	References
Adoption intention(ADI)	ADI1. If my bank were to provide a mobile banking app, I would use it immediately ADI2. If mobile banking apps become available, I would adopt them ADI3. I plan to increase my adoption of mobile banking apps in the future ADI4. I would use mobile banking apps because my family and friends do	Priya et al. (2018)

(continued)