



Effect of Artificial Intelligence Features on Users' Adoption Intentions of Mobile Banking Applications: Evidence from Egyptian Private Banks.

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Abstract

The main aim of this research is to advance understanding of the artificial intelligence features and its effects on adoption intention in the Egyptian private banks and minor aim examining if functional and psychological levels of evaluation have a mediating effect on the relation between artificial intelligence features and the adoption intention. The objectives of this research are: to examine the relationship between artificial intelligence features and the adoption intention, to test the relationship between artificial intelligence features and functional level of evaluation, to investigate the relationship between artificial intelligence features and psychological level of evaluation, to examine the relationship between functional level of evaluation and the adoption intention, to investigate the relationship between psychological level of evaluation and adoption intention, to examine the mediation role of functional level of evaluation between artificial intelligence features and adoption intention. Finally, to investigate the mediation role of psychological level of evaluation between artificial intelligence features and adoption intention. Data in this study came from a survey questionnaire of 445 acceptable responses. The results were analysed employing by Structural Equation Modeling technique (SEM) using Analysis Moment of Structures (AMOS) software. The main conclusions drawn from this study are: the direct effect between artificial intelligent features and adoption intention is statistically significant, the direct effect between artificial intelligent features and functional level of evaluation is statistically significant, the direct effect between artificial intelligent features and psychological level of Evaluation is statistically significant, the direct effect between functional level of evaluation and adoption intention is statistically significant, the direct effect between psychological level of evaluation and adoption intention is statistically significant. Moreover, the results of the mediation effect indicate that there is partial mediation effect of both functional and psychological levels of evaluation in the relationship between artificial intelligent features and adoption intention.

Keywords: *artificial intelligence features, adoption intention, banking sector.*

1. Introduction

In recent years, the continuous penetration of mobile technology into the financial and banking industries in recent years has transformed the traditional banking service provision method into a new modern banking technology supported by the internet (Gupta et al., 2019). In this context, both users and banks are interested in the emergence of mobile banking and the study of its adoption (Cao and Liu, 2018). Mobile banking removes the physical constraints of daily banking activities, allowing users to conduct their banking transactions whenever and wherever they want (Hassan and Wood, 2020). Furthermore, users can use mobile banking to conduct bank activities such as transferring funds, making investments, making payments, and checking account information on a regular basis (Owusu Kwateng et al., 2019), which provides a quick and efficient 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 (Suhartanto et al., 2021; Yussaivi et al., 2021). The use of intelligent machine performance and humanlike behavior to assist customers and improve their banking experience is referred to as AI (Prentice et al., 2019). AI can aid users in completing activities by comprehending their context, responding to their queries, and offering them support and value (Lin et al., 2021). The most logical manifestation of the development of AI is the transition from conventional mobile banking apps to modern intelligent apps (Lin et al., 2021). Artificially intelligent service algorithms handle data intelligently, evaluate users' emotions, and use natural language to provide personalised services and transactions when customers use mobile banking applications (apps) with AI (Zhu, 2018). Mobile banking services become more intelligent and human as a result of AI, which can also deliver anthropomorphic financial services (Jiang, 2018; Wang, 2017). Understanding how AI functions in mobile banking apps is crucial. The two primary AI traits of intelligence and anthropomorphism, which AI brings with it, constitute the major differences between artificially intelligent services and other systems (Lin et al., 2021; Moussawi et al., 2020). A system that is intelligent can assist users with financial services or chores by acting efficiently and on its own. Anthropomorphism describes a system that processes a service or job in a manner like that of humans (Lin et al., 2021). Numerous studies have looked at mobile banking within the framework of AI, but they have disregarded how AI elements in app evolution effect user adoption intentions (Manser Payne et al., 2018, 2021; Suhartanto et al., 2021). The intelligence and anthropomorphism constructs are therefore regarded as the key AI aspects in this study to investigate user intention to embrace AI-enabled mobile banking apps. Moreover, literature has shown that mobile banking users often consider functional and technical reasons (Gupta et al., 2019), including **task-technology fit (TTF)** (Baabdullah et al., 2019;), perceived cost (Owusu Kwateng et al., 2019) and perceived risk (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 (Zhang et al., 2018; Siyal et al., 2019; Hassan and Wood, 2020).

AI technology is now present in mobile banking. However, current research on mobile banking frequently views the growth of AI as a supporting factor or function (Suhartanto et al., 2021). Furthermore, it is unknown how users' perceptions of the functional level (i.e., TTF, perceived cost, risk) and psychological level (i.e. trust) of mobile banking apps are impacted by the AI traits of intelligence and anthropomorphism, necessitating further research and analysis. A research question is subsequently put out in light of the foregoing context: Do AI-based constructs (such as perceived intelligence and anthropomorphism) affect mobile banking app adoption intentions at the functional level (such as TTF, perceived cost, and risk) and psychological level (trust and emotional experience). The overall aim of this research is to advance understanding of the Artificial Intelligence Features and its effects on Adoption Intention in the Egyptian private banks and minor research investigating if Functional level of Evaluation and Psychological level of Evaluation have a mediating effect on the relation between Artificial Intelligence Features and the Adoption Intention.

2. Literature Review

Artificial Intelligence Features is considered as the independent variable, Functional level of Evaluation is considered as the first mediator variable, psychological level of Evaluation is considered as the second mediator variable, and Adoption Intention is considered as the dependent variable.

2.1 AI based mobile banking

AI is a cutting-edge technology that has been shown to have a substantial impact on a number of business sectors, including operation management, marketing, and retailing (Li et al., 2019), tourism and hospitality (Guha et al., 2021), and finance and banking (Milana and Ashta, 2021). (Turner et al., 2019). Machines with AI are described as having traits of human intelligence (Huang and Rust, 2021). Similar to humans, AI models use automation, big data, and machine learning to accomplish predetermined goals and tasks through computers and other devices (Prentice et al., 2019). Business procedures, goods and services, and user experiences have all been altered by AI. For instance, AI technology in marketing and commerce makes individualised offers to customers to improve their purchasing experience and engagement (Grewal et al., 2021). Banks can increase their online banking's speed, accuracy, and efficiency by implementing autonomous AI technologies that require no human intervention (Kaya, 2019). Also, studies have demonstrated that AI can help banks do real-time identification processing, which can help prevent fraudulent activities (such credit and financial statement fraud) in online banking transactions (Ricceri et al., 2021). According to Luo et al. (2020), using AI to improve the quality of online banking services and strengthen the safety of current online banking systems is possible. Artificial intelligence's (AI) practical connection to mobile banking has been further increased with the rapid growth of mobile technology, making studies of the two's interrelationship more important than ever. Artificial intelligence (AI) has been identified as a crucial component of mobile banking innovation (Huang et al., 2021). This is because AI can be used to enhance the user experience and the effectiveness of banking services, hence fostering closer connections between banks and their customers (Huang and Rust, 2020). If a user has an

issue while using their AI-enabled mobile banking app, they can immediately contact the app's AI-powered service for assistance (Zhu, 2018). Mobile banking apps with AI capabilities can generate exact queries and use natural language to help people throughout conversations and solve similar issues consistently. The objectives are to increase efficiency (Lin et al., 2021), eliminate the danger of human customer service subjective judgement errors, and produce results that are standardised, consistent, and dependable. Additionally, the apps can match different descriptions of different users who are experiencing the same issue and provide personalised benefits to identify and match them (Wiegard and Breitner, 2019). They can also provide the advantages of rationalisation and technical visualisations that fully reflect anthropomorphism (Li et al., 2019).

2.2 Functional and psychological factors

Researchers have demonstrated that functional and psychological perspectives are the main causes of resistance to the acceptance of innovations (Huang et al., 2021). Functional aspects involve three primary elements, according to Ram and Sheth's (1989) definitions: TTF, perceived cost, and risk. Researchers contend that risk, in the context of mobile banking, is a key predictor of users' perceptions of financial loss sustained, privacy being infringed, or personal data being abused (Priya et al., 2018; Siyal et al., 2019). Additionally, research has shown that understanding users' pricing perceptions is crucial since it affects how predictably consumers will comprehend and use mobile banking programmes (Owusu Kwateng et al., 2019). Additionally, earlier studies have used the TTF model to investigate how customers feel about the adoption of mobile banking (Baabdullah et al., 2019). Multiple factors can be combined to increase the explanatory power of user adoption intention, according to research (Tam and Oliveira, 2019). Functional characteristics (organic experiences) are thus further taken into account in this study to predict users' intentions to utilise AI mobile banking apps after being linked with risk, cost, and TTF. According to the available psychological literature, the biggest cause of psychological resistance to mobile banking innovation is the customers' lack of faith in it (Mehrad and Mohammadi, 2017; Sharma and Sharma, 2019). Trust is the most important predictor of m-commerce adoption since it significantly affects its success, according to Sarkar et al. (2020). Additionally, Bedue and Fritzsche (2021) shown that gaining trust is a key step toward greater AI-based adoption, which is why we selected trust as the model's primary psychological factor. Furthermore, a number of functional and psychological elements that affect consumers' adoption of mobile banking have been independently investigated by existing studies (Gupta and Arora, 2017), but no studies have incorporated these factors into a unified model. According to social psychology research, the factors that encourage and inhibit adoption may not always be mutually exclusive. The behavioural reasoning theory, which enables the simultaneous assessment of the influence of adoption and resistance factors in a model, can also be used to explain mobile banking (Gupta and Arora, 2017). In this regard, this study investigates the factors 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).

2.3 Anthropomorphism

The use of human-like features in technological artifacts like robots and personalized intelligent software systems (PIAs) aims to improve the agent's ability to engage in meaningful social interactions. Such interactions require the employment of human-like qualities in form or

behavior Duffy (2003). Anthropomorphism relates to the user's attribution of human capacities to a non-human agent. Objects are generally perceived to be humanlike when they possess features or characteristics that reflect emotions, cognition, or intention. Any object might be perceived to be human-like including cars and Coca-Cola bottles Aggarwal and McGill (2007). There are several approaches to conceptualising and measuring users' perceptions of the system's human-likeness. Kiesler et al. (2008) investigated the sociability, human likeness, and machine-likeness of robots, whereas Bartneck et al. (2009) investigated movement, artificialness, fakeness, and consciousness of robots. Waytz et al. (2014) emphasised the importance of mental capacities, arguing that the presence of mental capacities is both a necessary and sufficient condition for humanness.

2.4 Adoption Intention

Consumers embrace new technologies for different reasons. Well-known models in marketing and management indicate why new technologies tend to be adopted (e.g., perceived ease of use and perceived usefulness) and why they tend to be rejected for instance: salient financial and performance risks (Antioco and Kleijnen 2010) Arts (Thong, and Xu 2012). These models further show the moderating roles of consumer demographics (e.g., age) and psychographics (e.g., innovativeness) while highlighting the gap between adoption intention and behavior, with properties such as high innovation complexity increasing adoption intention but decreasing actual adoption Arts (Frambach, and Bijmolt 2011). Whereas some of these findings can be transferred to autonomous shopping systems, these systems likely display additional enablers of (and barriers to) adoption due to their unique characteristics—such as the delegation of the decision-making process. New technologies usually face difficulties in the market, illustrating the challenge of persuading users to adopt unique and unfamiliar technology. The high failure rate is a result of adoption barriers, which discourage customers from experimenting with new technology. One such hurdle is a lack of technological readiness, which can make using new technologies frustrating (Parasuraman 2000). Barriers to adoption are often not only functional but also psychological and cultural (Antioco and Kleijnen 2010). Thus, consumers may value the benefits of a new technology but may nevertheless not adopt it because of how they feel about the technology. This is in line with research highlighting that consumption is not only driven by functional aspects but also by playful and fun aspects (Okada, 2005).

3. Conceptual Framework

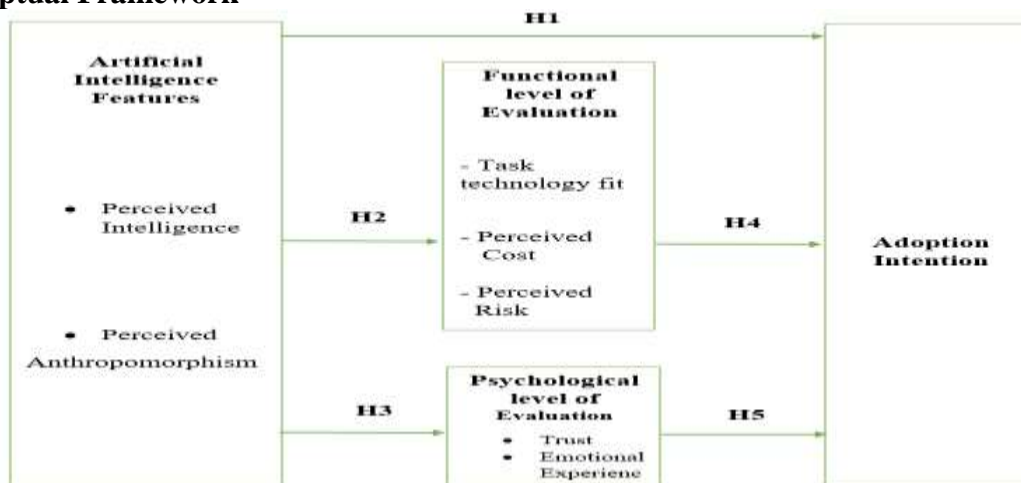


Figure 1- Conceptual Framework

4. Operational Definition

Variable	Measurement Scale
Independent Variable: Artificial Intelligence Features	Lin et al. (2021), Moussawi and Koufaris (2019)
Mediator: Functional level of Evaluation	Lin and Huang (2008); Hanafizadeh et al., (2014); Hassan and Wood (2020)
Mediator: psychological level of Evaluation	Hassan and Wood (2020); Van Wyk (2016)
Dependent Variable: Adoption Intention	Priya et al., (2018)

5. Research Methodology

For the purpose of this research, the research population refers to customers who deals with Egyptian private banks. The research questionnaire was administered to eight hundred (800) respondents, 487 questionnaires representing 60.1% were returned, and 42 questionnaires representing 5.3% were incomplete or ineligible or refusals and 313 (39.1%) were not reached. There were 445 acceptable responses, a response rate 55.6%, which is highly adequate for the nature of this study. In this Research Paper, the Amos software package was used to perform the structural equation modelling (SEM) to investigate the inter- relationships between the constructs of the hypothesized model. Hypotheses Testing Following a confirmatory factor analysis, the valuation of the structural model through testing of the hypotheses underlying the research model is conducted.

6. Results and Findings

Composite reliability (CR) is used to measure the reliability of a construct in the measurement model. CR of (Perceived intelligence = 0.921, Functional level of Evaluation =0.882, Perceived cost =0.873, Perceived risk = 0.841, Task technology fit = 0.926, Trust =0.827, Perceived Anthropomorphism = 0.887, Emotional Experience = 0.838 and Adoption Intention = 0.941). So, it clearly identified that in measurement model all construct have good reliability. The average variances extracted (AVE) should always above 0.50 (Hair et al., 2019). AVE of the particular constructs Perceived intelligence = 0.702, Functional level of Evaluation =0.882, Perceived cost =0.697, Perceived risk = 0.518, Task technology fit = 0.714, Trust =0.561, Perceived Anthropomorphism = 0.613, Emotional Experience = 0.566 and Adoption Intention = 0.727) are more than 0.500. Overall, these measurement results are satisfactory and suggest that it is appropriate to proceed with the evaluation of the structural model.

Measurement model Results: The 8 factor was subjected to CFA using the AMOS software. DF was 604 (it should be more than 0), χ^2 /DF has a value of 2.635, that is less than 3.0 (it should be less than or equal 3.0). The RMSEA was 0.059 (it should be less than 0.08). The TLI index was .917 which is very close to 1.0 (a value of 1.0 indicates perfect fit). The CFI was 0.925. All indices are close to a value of 1.0 in CFA, indicating that the measurement models provide good support for the factor structure determined through the CFA.

Structural model

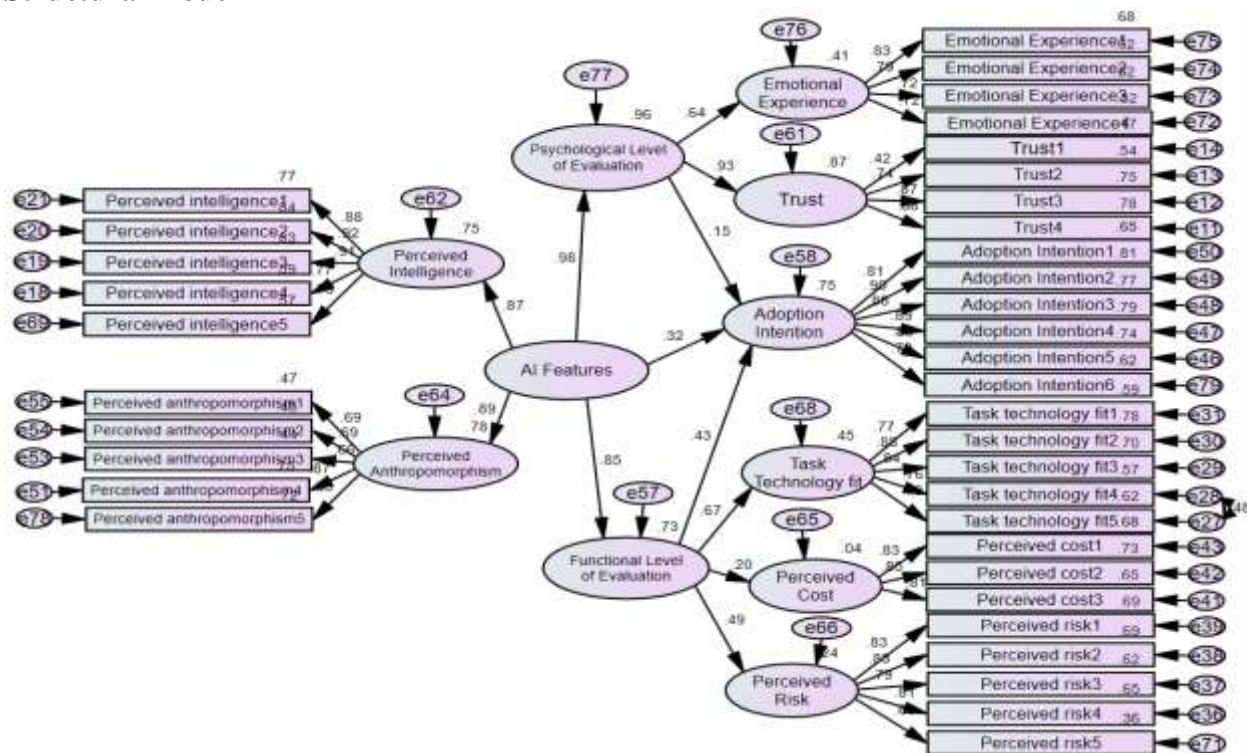


Figure (2) Structural Model (Final Result)

Structural model summary. The results of structural model using the AMOS software, shows that DF was 622 (it should be more than 0), χ^2 / DF has a value of 2.803, that is less than 3.0 (it should be less than or equal 3.0). The RMSEA was 0.061 (it should be less than 0.08). The TLI index was 0.908 which is very close to 1.0 (a value of 1.0 indicates perfect fit). The CFI was 0.914. All indices are close to a value of 1.0 in CFA, indicating that the measurement models provide good support for the factor structure determined through the CFA.

7. Discussion

This research study aimed at investigating the relationship between artificial intelligence features and adoption intention with mediation role of functional and psychological levels of evaluation in the Egyptian private banks. Users in different countries may show different perceptions and reactions to banking services (Malaquias and Hwang, 2019). 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., 2021), UK (Bholat and Susskind, 2021), or Australia (Argus and Samson, 2021). However, research on users' perception of AI banking services in the context of Egypt remains unexplored. Thus, this study attempts to emphasize Egyptian 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. Due to the individual tests of significance of the relationship between the variables. It reveals that, as expected a relationship between Artificial intelligent Features and Adoption Intention ($\beta = 0.320$, CR

(Critical Ratio) = 4.670, $CR > 1.96$, $p = 0.000$, $p < 0.05$). Therefore, (**H1**: Artificial Intelligence Features have an impact on Adoption Intention of mobile banking users in Egypt.) is supported. This result is consistent with Kaur et al. (2020aP) and Chau and Nagai, (2010) whom highlighted the importance of understanding the adoption of mobile financial services in the emerging markets given their ability to contribute to the economy and address the issues related to structural constraints. While mobile banking adoption has been extensively researched in developed countries. In addition, Scholars have pointed out that AI, as a key aspect of mobile banking innovation, 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; Huang 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). The apps are able to provide personalized benefits to identify and match different descriptions of different users with the same problem and provide the benefits of rationalization and technical visualizations fully reflect anthropomorphism (Li et al., 2019; Wiegard and Breitner, 2019; Manser Payne et al., 2021). Further, the result shows that **H2**: Artificial Intelligence Features have an impact on Functional level of Evaluation of mobile banking users in Egypt. ($\beta = 0.853$, CR (Critical Ratio) = 12.960, $CR > 1.96$, $p = 0.000$, $p < 0.05$). is supported, as it predicts that " There is a relationship between Artificial intelligent Features and Functional level of Evaluation". This result is consistent with Tam and Oliveira (2019) who confirmed that integrating multiple factors is helpful to maximize the explanatory power of user adoption intention. Existing studies have adopted the TTF model to explore users' evaluations of mobile banking adoption (Oliveira et al., 2014; Baabdullah et al., 2019). Above and beyond, exploring users' perceptions of cost is important because it determines the predictive ability for understanding and learning to use mobile banking apps (Haider et al., 2018; Owusu Kwateng et al., 2019; Merhi et al., 2019). Moreover, pertaining to **H3**: Artificial Intelligence Features have an impact on psychological level of Evaluation of mobile banking users in Egypt. ($\beta = 0.982$, CR (Critical Ratio) = 12.247, $CR > 1.96$, $p = 0.000$, $p < 0.05$). is supported, as it predicts that " There is a relationship between Artificial intelligent Features and Psychological level of Evaluation ". This result is consistent with Huang et al., (2021) who stated that, resistance to innovation adoption stems mainly from functional and psychological perspectives. 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 (Gupta et al., 2019; Malaquias and Hwang, 2019; Sharma and Sharma, 2019). Bedue and Fritzsche (2021); and Sarkar et al., (2020) 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. The result shows that **H4**: Functional level of Evaluation has an impact on Adoption Intention of mobile banking users in Egypt. ($\beta = 0.427$, CR (Critical Ratio) = 3.605, $CR > 1.96$, $p = 0.021$, $p < 0.05$). is supported, as it predicts that " There is a relationship between Functional level of Evaluation and Adoption Intention ". This result is consistent with (Manser Payne et al., 2018; Lin et al., 2020; Lin et al., 2021; Mohd Thas Thaker et al. ,2019; Baabdullah et al., 2019; Tam and Oliveira, 2019; Owusu Kwateng et al., 2019). Moreover, pertaining to **H5**: Psychological level of Evaluation has an impact on Adoption Intention of mobile banking users in Egypt ($\beta = 0.153$, CR (Critical Ratio) = 4.670, $CR > 1.96$, $p = 0.021$, $p < 0.05$). is supported, as it predicts that " There is a relationship between Psychological level of Evaluation and Adoption Intention ". This result is consistent with (Moussawi et al., 2020; Huang and Rust, 2021; Belanche et al., 2019; Milana and Ashta,

2021). Results reveal a statistically significant indirect effect between artificial intelligent features and adoption intention through functional level of evaluation ($P = 0.003$, $P < 0.05$). and a statistically significant indirect effect between artificial intelligent features and adoption intention through psychological level of evaluation ($P = 0.002$, $P < 0.05$). The results of the mediation effect indicate that there is *partial mediation* effect of the functional level of evaluation between the relationship of artificial intelligent features and adoption intention. This result is consistent with (Owusu Kwateng et al., 2019; Hassan and Wood, 2020). In addition to that, *partial mediation* effect of the psychological level of evaluation between the relationship of artificial intelligent features and adoption intention. This result is consistent with (Merhi et al., 2019; Sharma and Sharma, 2019; Cho et al., 2019; Chan et al., 2017). This paper has dual significance both academically and practically. Academically, the current research fills the gap and supplements the literature. The research developed a model contributes knowledge to other models that have recommended expanding the investigative scope using structural equation modelling technique. Therefore, an integrated framework estimated structural model corroborated the five hypotheses, as Artificial intelligent Features construct explained 72.7 % of Functional level of Evaluation variance ($R^2 = 0.727$), and Artificial intelligent Features construct explained 96.4 % of Psychological level of Evaluation variance ($R^2 = 0.964$). Besides, Artificial intelligent Features through Functional level of Evaluation and Psychological level of Evaluation explained 74.8 % of Adoption Intention variance ($R^2 = 0.748$). In addition to that, Lee and Chen (2022) considered trust as the only dimension of psychological level of evaluation. However, this paper contributed to the body of literature considering the effect of both emotional experience and trust as dimensions of psychological level of evaluation. Practically, the findings of this research have several implications for the development of the Egyptian private banks. This study provides practical reference significance for developing mobile banking services and promoting mobile banking app adoption. R&D employees should consider using AI technology while offering mobile banking services to better fulfill users' goals and objectives, reduce mistakes, and improve reliability. Innovative mobile banking technology or intelligence chatbots, for example, can be helpful to users handling regular difficulties; instead of waiting for manual service for a long time, they are conducive to accelerating mobile banking technology customer adoption and utilization. The aims are to include more intelligent components during the development of mobile banking apps, which will help improve efficiency while also assuring the completion of the user's banking business and will offer convenience to users while decreasing traditional bank labor costs. At the same time, the needs of clients are becoming increasingly diversified, which necessitates the need for personalized services. In terms of intelligence, mobile banking apps need to be able to address a user's personalised problems in a targeted manner, similar to how real-life interactions occur. These objectives provide banks with a direction when developing mobile banking apps: Add anthropomorphic elements such as voice and image to the software development process for mobile banking in order to provide more personalised services to consumers with added value. In addition to being reflected in the two-dimensional visual space of mobile banking, personification also introduces higher standards for deep learning feedback mechanisms, necessitating that banks capitalise on the continuous development and improvement of AI technology.

9. Limitations and future directions

Despite the fact that this study adds to theory and practice, some limitations still exist, opening possibilities for future research. First, this study's survey samples are conducted solely in Egypt;

consequently, the findings may lack generalizability. Future studies may duplicate this research in other countries or regions to acquire more generalizable results.

Second, AI-powered mobile banking apps are a type of financial innovation. According to several studies, younger people are more willing to embrace and accept innovative services (Lee and Chen, 2019, 2022). In this regard, future studies may consider age as a moderator for investigating and evaluating if the model differs significantly when applied to users of different ages.

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