PREPRINT

SOCIAL SCIENCES & HUMANITIES

Journal homepage: http://www.pertanika.upm.edu.my/

AI Banking Adoption in Saudi Arabia: Extending the UTAUT Framework

Sultan Alaswad Alenazi

Department of Marketing, College of Business Administration, King Saud University, 11362 Riyadh, Saudi Arabia

ABSTRACT

With the tremendous recent advances in Artificial Intelligence (AI), many businesses have begun to utilise it to improve their operations and enhance the customer experience. Utilising the unified theory of acceptance and use of technology (UTAUT) as a theoretical framework, the present study examines the behavioural intentions of Saudi customers towards AI-powered banking. The UTAUT model is extended by incorporating trust and perceived risk as additional factors influencing customers' behavioural intentions when using AI-powered banking, alongside perceived performance, perceived effort, and social influence. The participant sample for the study consisted of 323 bank customers. The findings of the structural equation modelling (SEM) analysis indicate that all the factors in the extended model affected customers' intention to use AI-powered banking. Specifically, perceived performance, perceived effort, social influence, and trust had positive effects on the intention to use, whereas perceived risk had a negative effect on this intention. These results underscore the importance of developing more user-friendly and effective AI-powered banking services. Additionally, the results demonstrate the effectiveness of targeting customers through key individuals in their lives to encourage their adoption of AI-powered banking. Finally, gaining customers' trust and lessening their perceived risk both increase their likelihood of using AI-powered banking.

Keywords: Artificial intelligence acceptance, perceived risk, trust, UTAUT

ARTICLE INFO

Article history:
Received: 21 November 2025
Accepted: 23 January 2026
Published: 19 February 2026

DOI: https://doi.org/10.47836/pjssh.34.1.12

E-mail address:
sualenazi@ksu.edu.sa (Sultan Alaswad Alenazi)

INTRODUCTION

Artificial intelligence (AI) is changing the way businesses operate and provide services to their customers. With a projected total contribution of USD 15.7 trillion to the global economy (Pavlidis, 2025), AI is expected to remain a key driver of

e-ISSN: 2231-8534

business development worldwide. Currently, services are increasingly enhanced with technology. Financial and banking services are key areas witnessing a rise in AI utilisation (Onabowale, 2024). Banks have transitioned from traditional operations and customer service to technology-based services, including ATMs, the internet, mobile banking, and AI-powered banking. Integrating AI into banking services has improved the way that banks operate and serve their customers, including through transaction automation, service personalisation, and financial advising (Sharma et al., 2024).

Although customer acceptance of new banking technologies, such as internet banking and mobile banking, has been extensively studied, the adoption of AI in banking from the customer perspective has not yet been fully explored. Therefore, this study aims to investigate the behavioural intentions of Saudi customers towards AI-powered banking. By shedding light on the adoption of AI-powered banking in a developing country like Saudi Arabia, this study aims to expand our understanding of the factors that enhance its acceptance. Although banks in Saudi Arabia have embraced other sophisticated technologies such as the internet and mobile banking, they remain far from optimally utilising AI in their banking services. Moreover, although AI offers numerous features for customers to utilise, not all opt to use it. Therefore, banks need to determine how customers perceive AI and understand their attitudes and intentions towards its use to increase AI adoption and enable the optimisation of AI-powered services to, which can ultimately enhance customers' banking experience.

Despite the growing integration of artificial intelligence (AI) in the global banking sector, customer adoption of AI-powered services remains low in several regions, including Saudi Arabia. While AI offers promising benefits—such as improved service efficiency, personalised financial recommendations, and cost reduction—many customers remain hesitant to engage with AI technologies. This hesitation is often attributed to concerns over trust, data privacy, usability, and risk perception. Existing research has primarily focussed on technology adoption in general or in Western contexts, with limited attention given to how cultural, social, and technological factors uniquely influence the acceptance of AI in banking across Middle Eastern societies. As a result, a significant knowledge gap exists regarding the drivers of and barriers to AI adoption in the Saudi banking context. Addressing this gap is crucial for informing banks, developers, and policymakers on how to tailor AI services to meet local user expectations and comply with relevant regulatory frameworks.

Moreover, despite the growing body of research applying the unified theory of acceptance and use of technology (UTAUT) and its extensions in digital and mobile banking contexts, limited empirical attention has been given to AI-powered banking services, particularly within emerging economies such as Saudi Arabia.

Unlike conventional digital banking, AI-enabled services rely heavily on automated decision-making, extensive data processing, and algorithmic interactions, which elevate the roles of trust and perceived risk in shaping user acceptance. This study contributes to the literature by empirically examining the relative explanatory power of traditional UTAUT constructs alongside trust and perceived risk in the context of AI-powered banking. By doing so, it provides context-specific evidence on whether trust and risk perceptions outweigh classical technology acceptance drivers in consumers' evaluation of AI-based financial services.

The remainder of this paper is organised as follows. First, the literature on AI banking is reviewed, followed by a discussion of UTAUT. The conceptual model is then presented, and the hypotheses are formulated. The methodology section presents the sample, data collection, data analysis, and results. The last section provides a discussion of the study's results, implications, and limitations.

LITERATURE REVIEW

Artificial Intelligence in Banking

AI has brought about a significant shift in multiple aspects of various industries. To remain competitive in today's market, businesses must adopt advanced technologies, such as AI. Considering recent advancements in AI technologies, many businesses have started to utilise them to reduce costs, improve their services, and enhance the customer experience (Pagani & Pardo, 2017; Parise et al., 2016; Ransbotham et al., 2017). In particular, the banking and financial services sector has increasingly adopted AI technologies. Some of AI's advantages include automation, fewer human errors, and the availability of 24/7 services (Ghandour, 2021). Additionally, AI enables banks to achieve their goals of high-speed, error-free services (Noreen et al., 2023) and prevent fraud by effectively predicting the credit risk of clients (Haro et al., 2018).

AI has also been widely used to automate bank operations (Agarwal, 2019) and reduce costs, with the latter stemming from distinct aspects of banking services. For example, the AI automation of customer services saves considerable costs in terms of human resource efforts and training, as chatbots and virtual assistants are more cost-effective options (Pattanayak, 2023). AI integration can also enhance customers' experience and improve their satisfaction (Maseke, 2024). AI enables banks to offer new features for their customers, including chatbots and robo-advisors (Indriasari et al., 2022). According to Misischia et al. (2022), integrating chatbots into banking services improves interaction, entertainment, and problem-solving.

Customers' behaviour towards AI-powered banking has been studied to understand their intention towards its use. In their study of Malaysian customers' adoption of AI banking, Rahman et al. (2023) identified perceived usefulness as the main factor affecting customers' intention to use AI banking, with customers' attitude towards AI banking mediating the effect. They also found that perceived risk had an adverse effect on the intention to use AI banking, while perceived trust and subjective norms had a positive effect. In a study of customers' usage of chatbots in banking services, Alt et al. (2021) found that perceived usefulness and perceived compatibility positively affect customers' intention to use chatbots. They also found that service awareness directly affects perceived ease of use and perceived privacy risk and indirectly affects use intention.

While AI offers advantages that can enhance customers' banking experiences, customers' adoption of AI is necessary for AI-powered banking services to be successful. Thus, as banks begin to offer such services, they must identify the factors that drive customer adoption and determine which AI characteristics are most important to customers. For example, attitudes towards AI, security, and trust have been found to influence customers' intentions towards using AI-powered banking services (Payne et al., 2018). Another factor that might affect AI adoption is customers' concern regarding the substantial amount of personal information required to provide them with tailored services (Hasan et al., 2023).

Unified Theory of Acceptance and Use of Technology

Venkatesh et al. (2003) proposed the UTAUT model to explain how users adopt modern technologies. UTAUT integrates eight theories on the adoption and acceptance of technologies by combining and synthesising important variables from each theory into a unified theory. These eight theories are the theory of reasoned action (TRA), theory of planned behaviour (TPB), technology acceptance model (TAM), motivational model (MM), combined theory of planned behaviour/technology acceptance model (C-TPBTAM), model of PC utilisation (MPCU), innovation diffusion theory (IDT), and social cognitive theory (Attuquayefio & Addo, 2014; Williams et al., 2015). The UTAUT model posits that the behavioural intention to accept technology is based on performance expectancy, effort expectancy, social influence, and facilitating conditions. The UTAUT model has been applied in various research areas, including healthcare technologies (Rouidi et al., 2022), food delivery mobile applications (Puriwat & Tripopsakul, 2021), and mobile banking (Yu, 2012). One of the main advantages of UTAUT is its capacity to incorporate other variables in explaining users' acceptance of modern technologies.

Study Hypotheses

According to the UTAUT model, technology acceptance is determined by four factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. This study focusses exclusively on the first three factors, as research has suggested that facilitating conditions influence actual use, not use intention (Venkatesh et al., 2003). Accordingly, facilitating conditions were excluded to maintain conceptual consistency with the study's focus on behavioural intention rather than actual usage behaviour in the context of

AI-powered banking. Although the proposed hypotheses are grounded in well-established technology acceptance research, their examination in the context of AI-powered banking remains theoretically meaningful. AI-enabled banking differs from earlier digital banking technologies in its reliance on automated decision-making, predictive analytics, and data-driven personalisation, which may alter the relative importance of traditional UTAUT predictors. Accordingly, this study does not aim to propose novel directional hypotheses but, rather, to assess the comparative strength of established relationships within an AI-specific and culturally distinct setting.

Performance Expectancy

Performance expectancy refers to users' perception of the benefits they derive from using a technology (Çalışkan et al., 2023). The effects of performance expectancy on technology acceptance have been consistently confirmed in studies across various industries, including the banking sector (Goswami & Dutta, 2016; Ivanova & Kim, 2022; Lakhal et al., 2013; Utomo et al., 2021). In their study of users' adoption of internet banking, Rahi et al. (2018) found that effort expectancy positively affected users' intention to use internet banking, and several other researchers came to the same conclusion (Dendrinos & Spais, 2024; Knutsen, 2005). Based on these findings, the following hypothesis is proposed:

> H1. Performance expectancy has a positive impact on customers' intention to use AI-powered banking services.

Effort Expectancy

Effort expectancy refers to users' perception of the ease of using a technology. Research has found that the intention to use a technology is higher when it is perceived to be easy to use (Ghalandari, 2012; Yu, 2012). In their study of behavioural intention to adopt digital banking among Vietnamese consumers, Nguyen et al. (2020) found that effort expectancy had a positive effect on consumers' intention to adopt digital banking. Similar findings were reported by other researchers (Foon & Fah, 2011; Hilal & Varela-Neira, 2022). Based on these findings, the following hypothesis is proposed:

> H2. Effort expectancy has a positive impact on customers' intention to use AI-powered banking services.

Social Influence

Social influence refers to the impact of influential individuals on a user's intention to adopt a technology. Yu (2012) found that social influence was the most influential variable in users' intention to adopt mobile banking. However, other studies have not found social influence to be a significant predictor of intention to adopt e-banking (Mhlanga & Langerman, 2024). Based on these findings, the following hypothesis is proposed:

> H3. Social influence has a positive impact on customers' intention to use AI-powered banking services.

Trust

Trust refers to the perceived mutual reliability and dependability between the parties involved in a transaction. Trust is a crucial factor in banking transactions (Skvarciany & Jurevičienė, 2018) and has been found to have a positive impact on the intention to use technology (Merhi et al., 2019). In a study of individuals' intention to adopt chatbots in banking, Yadav et al. (2024) found that trust had a positive effect on their intention. As trust is most important in technology adoption in the case of relatively modern technologies, including AI, the following hypothesis is proposed:

> H4. Trust has a positive impact on customers' intention to use AI-powered banking services.

Perceived Risk

Perceived risk refers to consumers' perception of the potential negative outcome of using a modern technology. Prior research has found that perceived risk negatively affects users' intention to adopt advanced technologies in banking services, such as the internet and mobile banking (Bashir & Madhavaiah, 2015). Thus, the following hypothesis is proposed:

> H5. Perceived risk has a negative impact on customers' intention to use AI-powered banking services.

METHODOLOGY

The current study used a quantitative method to evaluate the proposed model. The study population consists of Saudi bank customers who were at least 18 years old at the time of the study. Convenience sampling was used to collect survey data from a sample of 350 respondents via a survey shared on social media platforms. The answers of twenty-seven respondents were excluded due to incompleteness. Thus, the final sample consisted of 323 respondents. All respondents gave their consent to participate before completing the online survey.

Instrument

The first section of the questionnaire asked respondents to provide basic demographic information, such as age, gender, and education. The second section presented the measurement scales of the study variables. Likert-type scales (1 = strongly disagree; 5 = strongly agree) were used for all measurement scales.

All the scales were adapted from the extant literature. Performance expectancy (4 items), effort expectancy (4 items), and social influence (3 items) were measured using scales adopted from Venkatesh et al. (2003). Trust was measured using a 3-item scale adapted from Noh and Lee (2016). Perceived risk was measured using a 3-item scale adapted from Featherman and Pavlou (2003). Use intention was measured using a 3-item scale adapted from Bryson et al. (2015).

The survey was first developed in English, then translated into Arabic, and finally back translated into English. Two marketing academics assessed the face validity of the survey and provided feedback to enhance its quality. The revised survey was pretested with fifteen participants, who confirmed its appropriateness and clarity. When responding to the questionnaire, participants were instructed to consider common AI-enabled banking services, such as chatbots, virtual assistants, AI-based customer support, automated financial advice, and intelligent transaction services.

Analysis

SPSS and AMOS were used to evaluate the proposed model of interrelationships between performance expectancy, effort expectancy, social influence, trust, perceived risk, and customers' intention to use AI-powered banking services. Composite reliability (CR) and Cronbach's alpha were used to assess construct reliability. The Fornell-Larcker criterion and heterotrait-monotrait ratio (HTMT) were used to test the discriminant validity of the constructs. Finally, the Comparative Fit Index (CFI), Normed Fit Index (NFI), Root Mean Square Error of Approximation (RMSEA), and $\chi 2$/df were used to evaluate model fit.

RESULTS

As shown in Table 1, 58% of respondents were female, and 42% were male. Regarding age, 7% of respondents were 18 to 24 years old, 19% were 25 to 34 years old, 20% were 35 to 44 years old, 19% were 45 to 54 years old, 15% were 55 to 64 years old, and 20% were 65 years old or older. In terms of education, most respondents had a bachelor's degree or higher.

Table 1
Respondents' demographics

Demographic	Number of Participants
Gender	
Male	136
Female	187
Age	
18-24	22
25-34	60
35-44	67
45-54	62
55-64	48
65 and above	64
Education	
High school, no diploma	8
High school	43
College	66
Associate's degree	37
Bachelor's degree	96
Master's degree	53
Doctoral or professional degree	20

As shown in Table 2, Cronbach's alpha and CR for all constructs exceeded the recommended value of 0.70. The average variance extracted (AVE), as shown in Table 2, ranged from 0.77 to 0.89, exceeding the recommended value of 0.50, thereby providing evidence of convergent validity. Although some constructs exhibit high AVE values, this reflects strong convergence among items rather than redundancy. All measurement items were adapted from well-established and previously validated scales and were retained in their original form to preserve content validity. Moreover, the evidence from the Fornell-Larcker criterion and HTMT ratios confirms that the constructs remain empirically distinct, indicating that the high AVE values do not compromise discriminant validity. Specifically, the AVE square root of each construct is greater than the correlation of that construct with other constructs. The HTMTs of the constructs were less than 0.90. These findings provide evidence of the constructs' discriminant validity. Although some constructs exhibit high correlations, this pattern is common among theoretically related variables in UTAUT-based models.

Table 2
Construct reliability and convergent validity

Construct	Cronbach's Alpha	Composite reliability	Average Variance Extracted (AVE)
Effort expectancy	0.930	0.931	0.772
Performance expectancy	0.943	0.944	0.807
Perceived risk	0.941	0.941	0.842
Social influence	0.959	0.959	0.885
Trust	0.944	0.945	0.851
Use intention	0.959	0.960	0.888

Table 3
Fornell-Larcker criterion

Construct	Effort Expectancy	Performance Expectancy	Perceived Risk	Social Influence	Trust	Use Intention
Effort expectancy	0.879					
Performance expectancy	0.831	0.898				
Perceived risk	−0.441	−0.523	0.918			
Social influence	0.713	0.792	−0.645	0.941		
Trust	0.794	0.880	−0.584	0.859	0.923	
Use intention	0.809	0.875	−0.608	0.828	0.886	0.942

Multicollinearity concerns were evaluated through discriminant validity assessments using the Fornell-Larcker criterion and HTMT ratios, both of which fell within acceptable thresholds. These results suggest that the constructs remain empirically distinguishable and that multicollinearity is unlikely to bias the structural path estimates. Detailed discriminant validity statistics are reported in Table 3 and 4. In addition, supplementary collinearity diagnostics indicated that variance inflation factor (VIF) values for the structural predictors were within acceptable thresholds, further confirming that multicollinearity does not bias the estimated relationships.

Model Fit

The results show that the data fit the proposed model adequately. Specifically, $\chi^2/df = 2.06$, meeting the recommended value of < 3; GFI = 0.91, meeting the recommended value of > 0.90; AGFI = 0.88, meeting the recommended value of > 0.80; NFI = 0.961, meeting the recommended value of > 0.90; and RMSEA = 0.058, meeting the recommended value of < 0.08.

Hypothesis Testing

As summarised in Table 5, all hypothesised relationships were statistically significant and in the expected directions. Performance expectancy was found to have a positive

Table 4
Heterotrait-monotrait ratio (HTMT)

Construct	Effort Expectancy	Performance Expectancy	Perceived Risk	Social Influence	Trust
Performance expectancy	0.830				
Perceived risk	0.439	0.517			
Social influence	0.717	0.789	0.657		
Trust	0.792	0.881	0.593	0.857	
Use intention	0.813	0.874	0.607	0.841	0.895

Table 5
Structural model results and hypothesis testing

Hypothesis	Path	β	p-value
H1	Performance expectancy → Use intention	0.323	< 0.001
H2	Effort expectancy → Use intention	0.215	< 0.005
H3	Social influence → Use intention	0.139	< 0.05
H4	Trust → Use intention	0.335	< 0.001
H5	Perceived risk → Use intention	−0.110	< 0.005
H1	Performance expectancy → Use intention	0.323	< 0.001

effect on customers' intention to use AI-powered banking services (β = 0.323, $p < 0.001$), supporting H1. H2, which proposed that effort expectancy has a positive effect on customers' intention to use AI-powered banking services, was also supported, with β = 0.215 ($p < 0.005$). H3 proposed that social influence has a positive effect on customers' intention to use AI-powered banking services, and the results support this hypothesis as well (β = 0.139, $p < 0.05$). H4 proposed that trust has a positive effect on customers' intention to use AI-powered banking services, and the results support this hypothesis, with β = 0.335 ($p < 0.001$). Finally, H5 proposed that perceived risk has an adverse effect on customers' intention to use AI-powered banking services, which the results also support (β = −0.110, $p < 0.005$).

DISCUSSION

A comparison of the standardised path coefficients provides additional insight into the relative importance of the predictors of AI-powered banking adoption. Trust emerged as the strongest determinant of use intention (β = 0.335), followed closely by performance expectancy (β = 0.323), highlighting the significant role of confidence in AI systems and perceived functional benefits. Effort expectancy exerted a moderate effect (β = 0.215), suggesting that ease of use remains important but secondary to trust and performance considerations. Social influence showed a smaller yet statistically significant effect (β = 0.139), indicating a supportive rather than dominant role. As expected, perceived risk negatively influenced use intention (β = −0.110), reinforcing its role as a barrier to rather than a primary driver of adoption. Regarding perceived risk, the negative effect on use intention suggests that Saudi customers remain sensitive to potential uncertainties associated with AI-powered banking. In the local banking context, such risk perceptions are likely to stem from concerns related to data privacy, cybersecurity, automated decision-making, and the use of personal financial information by intelligent systems. Although perceived risk was modelled as a direct predictor in the current study, it is plausible that trust may partially mitigate these concerns by reducing customers' uncertainty and perceived vulnerability. Exploring the specific dimensions of perceived risk and the potential indirect role of trust represents a promising avenue for future research.

Theoretical Implications

AI-powered services are increasingly offered by service providers across various sectors, including banking, with many banks adopting AI in their operations and customer service. Despite the revolutionary features introduced by incorporating AI into banking services, the customer acceptance of AI-powered banking remains to be fully explored. To assess users' acceptance of AI in banking, this study used the UTAUT model, proposed by Venkatesh et al. (2003), to explain users' behavioural intention towards AI technologies. The results of the current study indicate that trust had the most significant effect on customers' intention to use AI-powered banking services, followed by performance expectancy, effort expectancy, and social influence. On the other hand, perceived risk, as hypothesised, had a negative effect on customers' intention to use AI-powered banking services. This result could be attributed to the growing importance of the financial aspect of banking services, as well as increasing customer sensitivity regarding the security of their transactions. The results of the current study align with those of previous studies, including those by Rahi et al. (2018), Nguyen et al. (2020), Yu (2012), and Yadav et al. (2024).

Theoretically, the current study adds to our knowledge by examining the UTAUT model to explain Saudi customers' acceptance of AI-powered banking services. The UTAUT model proved to be appropriate for explaining Saudi customers' intention to adopt these services. Another theoretical contribution of the current study is its expansion of the UTAUT model to include trust and perceived risk as factors affecting customers' intention to use AI-powered banking services. The UTAUT factors of performance expectancy, effort expectancy, and social influence, as well as the additional factors of trust and perceived risk, were found to influence customer acceptance.

Trust emerged as the most influential determinant positively shaping customers' behavioural intentions towards AI-powered banking services. Accordingly, it is essential for financial institutions to proactively disclose their AI usage policies, emphasising transparency, accountability, and ethical data handling to foster customer confidence and credibility. Additionally, targeted educational initiatives are recommended to enhance customers' understanding and perception of AI, which can significantly improve trust and facilitate broader adoption. Performance expectancy was identified as the second most significant predictor of AI banking adoption, underscoring the need for banks to prioritise efficiency, responsiveness, and functionality in their AI applications. This predictor was followed by effort expectancy and social influence, reinforcing the importance of designing AI interfaces that are intuitive, user-friendly, and accessible to a wide demographic. Furthermore, social influence was found to play a supportive role in shaping customers' intentions, suggesting that peer endorsements and social norms can complement, rather than dominate, individual evaluations of AI-powered banking services. The study also revealed that perceived risk exerts a negative impact on customers' intention to adopt AI-enabled banking technologies. Therefore, reducing perceived risk through enhanced cybersecurity measures, robust privacy safeguards, and customer assurance mechanisms is vital for promoting trust and reducing resistance. Overall, these findings underscore the multifaceted nature of technology acceptance in the context of AI banking and suggest a strategic approach for banks seeking to enhance customer adoption rates.

Practical Implications

The findings of this study yield several practical insights for banking institutions and policymakers aiming to facilitate the adoption of AI-powered services in Saudi Arabia and similar emerging economies. Most notably, the dominant role of trust as a predictor of behavioural intention emphasises the urgent need for banks to establish transparent AI usage policies and to actively communicate their ethical and secure handling of customer data. Practical steps may include publishing clear AI governance frameworks, embedding explainability features into AI systems, and offering customer assurance mechanisms. Furthermore, banks should invest in public education initiatives, such as digital literacy workshops, instructional videos, and in-app tutorials, which help demystify AI technologies and foster greater user confidence. These initiatives not only reduce psychological barriers but also strengthen user engagement and acceptance.

Additionally, enhancing the perceived performance of AI systems is crucial. Banks should focus on delivering services that are not only fast and dependable but also personalised and contextually relevant, reinforcing customers' perception that AI enhances service quality and convenience. Simplifying system interfaces to reduce cognitive load will help address concerns about effort expectancy, particularly for users with limited technological experience. The findings also suggest that social influence plays a non-trivial role in shaping customer decisions. Therefore, banks may benefit from strategies such as influencer engagement, referral programs, or testimonials that leverage trusted social networks to encourage adoption.

Finally, the negative impact of perceived risk on adoption intention highlights the importance of proactively addressing security concerns. Visible cybersecurity features, third-party certifications, and transparent privacy policies can help mitigate user concerns. In sum, a multi-faceted implementation strategy that prioritises trust, usability, social influence, and risk reduction is crucial for banks seeking to integrate AI technologies into mainstream financial services successfully. These practical implications can inform managerial decisions and policy design in the broader context of digital transformation and financial inclusion.

CONCLUSION, LIMITATIONS, AND FUTURE RESEARCH

This study examined the factors that affect customers' intention to use AI-powered banking. Using UTAUT, the results show that trust, performance expectancy, effort expectancy, and social influence had positive effects, while perceived risk had a negative effect, on AI-powered banking use intention. Understanding the factors that affect AI-powered banking use intention can help banks develop their AI-powered banking services in a way that appeals to customers.

Although the current study sheds light on customers' acceptance of AI-powered banking services, the results apply only to Saudi customers.

Thus, future research should replicate this study in other countries. The use of convenience sampling through online platforms may also limit the generalisability of the findings beyond the sampled respondents; future studies could employ probability-based or mixed sampling approaches to enhance external validity. In addition, the current study expanded the UTAUT model by incorporating trust and perceived risk as factors influencing customers' intention to use AI-powered banking services. Future studies may consider adding other factors, such as innovativeness, to the model to deepen our understanding of customers' intentions regarding the use of AI-powered banking services. In addition, future research could examine potential moderating variables, such as age, digital literacy, and prior experience with AI technologies, and employ alternative research designs, including longitudinal or experimental approaches, to further extend the current findings.

ACKNOWLEDGEMENT

The author extends his appreciation to the Deanship of Scientific Research, King Saud University, for supporting this project.

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