International Journal of Application on Economics and Business (IJAEB)
Volume 3, Issue 1, 2025. ISSN: 2987-1972

DOES AGE INFLUENCE AI-ENABLED MOBILE BANKING APP USAGE? ANALYZING COGNITIVE FACTORS AND SUSTAINED INTENTIONS

Yeo Chu-May Amy[1*], Lee Ee Chee2, Ong Yu Yan[3]

[1] Faculty of Accountancy, Finance and Business, Tunku Abdul Rahman University of Management and Technology, Malaysia
Email: yeocm@tarc.edu.my
[2] Chin Hin Group Bhd, Malaysia
[3] Asia Pacific University, Malaysia

*Corresponding Author

Submitted: 07-12-2024, Revised: 11-01-2025, Accepted: 24-02-2025

ABSTRACT

This research investigates the impact of cognitive aspects and AI attributes on the continued adoption of AI-powered mobile banking applications in Malaysia. It examines the relatively recent incorporation of AI into Malaysian mobile banking and the extent to which age influences user intentions. A total of 398 participants were surveyed, with data analysis conducted using SPSS. The results indicate that factors such as perceived usefulness, ease of use, enjoyment, and intelligence significantly contribute to users' continued engagement with AI-enabled banking apps, with age playing a moderating role. However, perceived anthropomorphism did not have a statistically significant effect on user intention, nor did age significantly moderate the connection between perceived intelligence and continuance intention. The study's findings aim to enhance AI-enabled banking applications, fostering a more user-friendly and satisfying experience across different age groups. These insights provide valuable direction for software developers and financial institutions aiming to optimize user satisfaction and engagement with AI-powered mobile banking systems.

Keywords: *AI-enabled mobile banking, continuance intention to use, perceived usefulness, perceived ease of use, perceived enjoyment, perceived anthropomorphism, perceived intelligence.*

1. INTRODUCTION

The evolution of artificial intelligence (AI) has significantly influenced various sectors, including manufacturing, retail, and financial services. AI's capability to simulate human behavior with minimal intervention has positioned it as a crucial tool for business operations (Rahman et al., 2021). Concurrently, mobile technology has transformed traditional banking services, leading banks to adopt AI-driven systems to enhance operational efficiency and remain competitive (Lee & Chen, 2022). AI-powered banking solutions streamline processes, extend service availability beyond regular banking hours, and enhance customer experiences. Financial experts emphasize AI's potential in personalizing banking services, making them more responsive to user needs (Sheth et al., 2022; Abdulquadri et al., 2021).

Indeed, electronic banking is now vital in global e-commerce due to the growth of online transactions and its role in facilitating financial transfers, highlighting its essential role in the e-commerce ecosystem. Furthermore, the rapid advancement of information technology has brought significant changes to banking, including the transformation of money and currency forms and the evolution of transfer systems (Danyali, 2018). Also, electronic banking enables secure access to banking services without physical visits to a bank (Salhieh et al., 2011). While, mobile-based banking apps have further revolutionised the industry, offering convenient fund transfers, investment opportunities, and account management (Hassan & Wood, 2020; Kwateng et al., 2019).

In fact, investments of approximately $11 billion in AI by the financial industry in 2020 indicate the sector's commitment to AI adoption (Bergur Thormundsson, 2022). It can be observed that the banking sector is aggressively developing AI in its business to adapt to current and future trends. Undoubtedly, users' confidence in AI's integration and application plays a pivotal role in its successful adoption in mobile banking services (Modiba, 2023). Additionally, age significantly influences technology acceptance, particularly in differentiating the behaviours of different generations, despite the increasing rapidity of new technologies (Yang & Shih, 2020). The profound significance of AI in mobile banking lies in its ability to mirror human comprehension and perception, particularly in attributes like anthropomorphism and intelligence. Despite, AI-enabled banking services can be complex, the anticipation is that they will enrich the overall customer experience (Lee & Chen, 2022; Sheth et al., 2022).

Moreover, existing literature suggests that users of AI-enabled applications often consider cognitive factors such as perceived usefulness (Hidayat-ur-Rehman et al., 2021; Yuan et al., 2016), perceived ease of use (Zhang et al., 2018), and perceived enjoyment (Ashfaq et al., 2020; Lin et al., 2017), which can influence their intention to continue using these AI applications. Additionally, AI features related to anthropomorphism and intelligence can impact users' perceptions and their intention to continue using AI-enabled applications (Balakrishnan et al., 2022).

Based on these observations, the research question is proposed: Do perceived usefulness, perceived ease of use, perceived enjoyment, perceived anthropomorphism, perceived intelligence, and age affect continuance intention to use? This exploration draws upon the foundational insights of the Technology Acceptance Model (TAM) and the comprehensive framework of the Extended meta-Unified Theory of Acceptance and Use of Technology Model (Extended Meta-UTAUT), guiding the development of the research framework and associated hypotheses.

Research Model Development

The research model is presented in Figure 1. This model leverages the TAM framework to assess the influence of perceived usefulness, ease of use, and enjoyment on continued AI-enabled banking app usage. Furthermore, the Extended Meta-UTAUT framework is employed to examine the roles of perceived anthropomorphism and intelligence. Age serves as a moderating factor, potentially influencing these relationships.

Perceived usefulness reflects users' belief in an application's effectiveness in meeting their financial needs (Bhattacherjee, 2001). It significantly influences user adoption and sustained engagement (Shih, 2004). When users find AI-powered banking apps beneficial, their likelihood of continued usage increases (Hidayat-ur-Rehman et al., 2021; Yuan et al., 2016). Therefore, this leads to the formulation of the following hypothesis:
H1: Perceived usefulness is positively related to continuance intention to use.

The importance of user-friendly technology in the adoption of new technology highlights the significant impact of perceived ease of use on customer intention and loyalty to mobile apps (Zhang et al., 2018). Likewise, it also stresses the critical role of perceived ease of use in driving customer intent and fostering loyalty to mobile apps (Ashfaq et al., 2020). Furthermore, ensuring a comprehensible and transparent service that facilitates seamless task completion is crucial for sustaining user intent (Ashfaq et al., 2020). In essence, user-friendliness strongly influences mobile banking adoption, significantly impacting users' determination to continue using the service (Jo, 2023). Therefore, based on these observations, we hypothesise that:

H2: Perceived ease of use is positively related to continuance intention to use.

Extensive literature supports the idea that users' intrinsic enjoyment and the overall pleasure derived from using a system significantly influence their intention to continue using it. In some cases, users engage with technology for entertainment and enjoyment, not just for performance (McLean et al., 2020; Ashfaq et al., 2020). Multiple studies confirm that perceived enjoyment is a crucial predictor of users' intention to continue using technology, especially in tech-related contexts (Ashfaq et al., 2020; Lin et al., 2017). When users interact with AI-enabled apps, a delightful and pleasurable experience can evoke positive sentiments (Ashfaq et al., 2020; Chung et al., 2020). In summary, individuals who find technology use enjoyable and fun are more likely to continue using it (To & Trinh, 2021). Consequently, we hypothesise that:
H3: Perceived enjoyment is positively related to continuance intention to use.

Consumers often develop anthropomorphic connections with technology, which can lead to increased brand loyalty over time. AI-enabled apps use various elements like names, tags, avatars, and emoticons during interactions, which users become accustomed to and form connections with (Balakrishnan et al., 2022; Chandler & Schwarz, 2010). The incorporation of anthropomorphic features boosts users' confidence and sense of control, resulting in a positive response to the technology (Pillai & Sivathanu, 2020). Furthermore, anthropomorphism simplifies the adoption and use of technology by leveraging our familiarity with human-like traits to understand the behaviour of non-human agents like AI-powered systems (Grazzini et al., 2023). This, in turn, encourages users to continue using AI-enabled apps (Balakrishnan et al., 2022; Chandler & Schwarz, 2010). It is evident that human-like traits are expected to promote the continued use of AI-enabled mobile banking apps, leading to our hypothesis that:
H4: Perceived anthropomorphism is positively related to continuance intention to use.

Intelligent systems, such as AI-enabled apps, offer substantial advantages by adapting to users' evolving needs through self-learning characteristics This adaptability is readily perceived by users and motivates them to continue using these apps (Balakrishnan et al., 2022; Shim & Jo, 2020). Intelligent systems also significantly enhance user experiences in various aspects of daily life, touching every facet (Malhotra & Ramalingam, 2023; Spanaki et al., 2022). Moreover, user interactions with these systems play a crucial role in improving AI's performance and intelligence, making it an essential part of users' decision-making processes and daily life (Malhotra & Ramalingam, 2023; Seeber et al., 2020). The personalised experiences offered by AI-enabled apps empower users and encourage continued utilization (Montes & Goertzel, 2019). Based on these insights, we hypothesize that:
H5: Perceived intelligence is positively related to continuance intention to use.

Recent research reveals significant age-related disparities in technology interactions (Chawla & Joshi, 2020). Younger adults exhibit expertise and a strong attraction to new technologies, emphasising practical benefits (Larson, 2020). In contrast, older adults contemplate technology differently, often influenced by familial preferences (Chung et al., 2010), and may not fully grasp advanced innovations (Wong et al., 2018). In addition, older individuals encounter challenges with mobile apps compared to tech-savvy younger users (Wong et al., 2018), which is attributed to younger individuals' interest and adaptability (Wonseok et al., 2021). However, younger adults display enthusiasm towards adopting new gadgets and prioritise factors such as price and specifications over ease of use. On the other hand, older adults prioritise ease of use over other considerations (Iancu & Iancu, 2020; Naqvi et al., 2020; Chung et al., 2010).

Besides, younger individuals derive pleasure from using mobile apps, even incorporating them into daily activities (Mehra et al., 2022). The COVID-19 pandemic further amplified these age-related differences, with younger people adapting more readily to e-commerce and new mobility services (Liu et al., 2021). Conversely, some older individuals may express frustration with new technology used by younger generations but can still find enjoyment in using mobile apps (Liu et al., 2021; Chawla & Joshi, 2020).

Then, in the realm of anthropomorphism, age also plays a role. Younger individuals tend to be more receptive to feelings, while older individuals exhibit a balance between feelings and thoughts (Letheren et al., 2016). Contrarily, older people may have a stronger inclination to anthropomorphise applications (Blut et al., 2021; Kamide et al., 2013). In fact, voice assistants offer socioemotional support to the elderly, aiding in alleviating loneliness (Pradhan et al., 2019). Additionally, older individuals perceive AI as an assistant, a tool that mimics human intellect and may have challenges in fully understanding AI-enabled mobile apps due to their limited familiarity with advanced app features (Shandilya & Fan, 2022). These age-related differences impact the adoption and intention to continue using AI-enhanced apps (Kim et al., 2022; Pillai & Sivathanu, 2020).

Clearly, different age groups may have diverse perspectives towards AI-enabled apps. Hence, we hypothesised that.
H6: The influence of perceived usefulness on continuance intention varies across different age groups.
H7: Age plays a moderating role in the relationship between perceived ease of use and the intention to continue using AI-enabled mobile banking apps.
H8: The extent to which perceived enjoyment impacts continuance intention is influenced by age differences.
H9: Age moderates the effect of perceived anthropomorphism on users' intention to sustain their use of AI-powered mobile banking apps
H10: Age Moderates the Relationship Between Perceived Intelligence and Continuance Intention to Use.

The formation of theoretical framework as indicated in Figure 1 below.

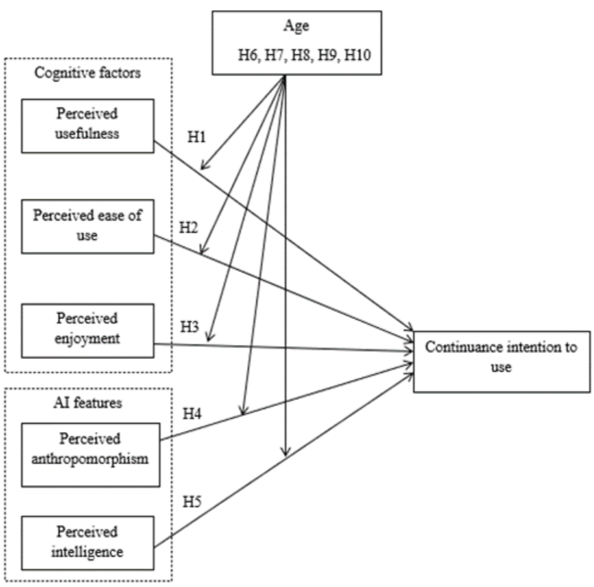

Figure 1. Research Framework

2. RESEARCH METHOD

Data collection and sample

This study uses a single cross-sectional design and survey data collection methods to gather its information. The target sampling for this research is Malaysian mobile banking users. The questionnaires have been designed according to the recommendations of Illum et al. (2010), Belanche et al. (2019), and Lee and Chen (2022). These suggestions focus on keeping the questionnaires concise and easy to understand, ensuring that the length is controlled. With the assistance of a professional online survey service provider such as Google Forms, respondents can promptly receive the survey form, allowing us to obtain data from them quickly (Lin & Lee, 2023). This is facilitated by sending the survey form's URL and QR code via social media platforms. Before creating the final questionnaire, a pilot test was conducted to identify and correct any faults or errors. Our survey ensures complete respondent anonymity and exclusively uses the data for academic research. This approach encourages honest participant responses and safeguards personal identities and privacy with strict confidentiality measures.

Selecting the right sample size is crucial for study validity and ethics. Too large or too small a sample can compromise rigour (Andrade, 2020). A well-chosen sample size prevents biases and errors (Taherdoost, 2017) and statistical formulas maintain population representation (Khalilzadeh & Tasci, 2017). Inadequate sample sizes yield weak and inconclusive results. Larger samples may not always offer better insights and can waste time and resources (Tripathi et al., 2020). Azeem et al. (2021) recommend a sample size exceeding 30 but below 500 for robust studies, also maintaining 200 or more participants in research ensures accurate and trustworthy insights into variable relationships, particularly in routine research situations (Hoque & Sorwar, 2017; De Winter et al., 2016). Indeed, this research has successfully gathered a total of 398 responses, meeting the prescribed sample size criteria, and thus, the sample is deemed suitable for comprehensive data analysis. The demographic information of accepted responses is presented in Table 1.

Table 1. Demographic Information of The Sample

Demographic Variables	Frequency (n=398)	Percentage
Gender		
Male	170	42.7
Female	228	57.3
Age		
18-24 years old	200	50.3
25-34 years old	63	15.8
35-44 years old	58	14.6
45-54 years old	44	11.1
55 years old and above	33	8.3
Average monthly income		
RM0-RM1000	141	35.4
RM1001-RM2000	31	7.8
RM2001-RM3000	29	7.3
RM3001-RM4000	41	10.3
RM4001-RM5000	77	19.3
RM5001 and above	79	19.8
Education background		
SPM	48	12.1
Foundation	11	2.8
Diploma	80	20.1
Bachelor's degree	233	58.5
Master's degree	20	5.0
PhD/ DBA	6	1.5

Frequency of using mobile banking		
Less than once per year	3	0.8
Two or three times per year	10	2.5
Two or three times per quarter	17	4.3
Two or three times per month	79	19.8
Two or three times per week	163	41.0
Every day	104	26.1
Never	22	5.5

3. RESULTS AND DISCUSSIONS

This study utilised Statistical Package for Social Science (SPSS) software to analyse data. SPSS will facilitate the organisation of the responses into easily interpretable tables, enabling meaningful insights to be extracted from the data. By conducting these analyses, the research aims to unveil the intricate relationships among the dependent variable, independent variable, and moderating variable within the study.

The analysis of multicollinearity in the study shows that all variables related to tolerance value (TV) have values between 0.325 and 0.607, and the variance inflation factor (VIF) for these variables ranges from 1.647 to 3.073. Notably, all TV values exceed the threshold of 0.1, while all VIF values are below the recommended threshold of 5, as suggested by prior researchers (Shrestha, 2020; Hair et al., 2011; Pan, 2010; Chen et al., 2008). The study, as indicated in Table 3, does not have any multicollinearity issues.

Table 3. Multicollinearity Analysis

Model		Collinearity Statistics	
		Tolerance Value (TV)	Variance Inflation Factor (VIF)
T_CI	T_PU	.496	2.016
	T_PEU	.360	2.778
	T_PE	.325	3.073
	T_PA	.556	1.798
	T_PI	.607	1.647

Note: T_CI=Total Continuance Intention to Use, T_PU=Total Perceived Usefulness, T_PEU=Total Perceived Ease of Use, T_PE= Total Perceived Enjoyment, T_PA=Total Perceived Anthropomorphism, T_PI=Total Perceived Intelligence

Considering the data presented in Table 4, the following correlations were identified. Rungskunroch et al. (2022) state that an 'r' value of 0.1 is a small correlation, 0.3 is a moderate correlation, and 0.5 is a substantial correlation. So, all constructs in the study exhibited either strong or moderate correlations with one another.

Table 4. Correlation Analysis

Constructs	T_PU	T_PEU	T_PE	T_PA	T_PI	T_CI
T_PU	1					
T_PEU	.688**	1				
T_PE	.623**	.747**	1			
T_PA	.434**	.493**	.626**	1		
T_PI	.425**	.478**	.576**	.544**	1	
T_CI	.555**	.586**	.565**	.389**	.510**	1

**. Correlation is significant at the 0.01 level (2-tailed).

Note: T_CI=Total Continuance Intention to Use, T_PU=Total Perceived Usefulness, T_PEU=Total Perceived Ease of Use, T_PE= Total Perceived Enjoyment, T_PA=Total Perceived Anthropomorphism, T_PI=Total Perceived Intelligence

Examinations of reliability and validity are essential to ascertain the accuracy of the variables. Cronbach's Alpha is employed to evaluate the reliability of the measurement scales, and as indicated in Table 5, Cronbach's Alpha values surpass the threshold of 0.70, in alignment with the recommendations of Hair et al. (2016). The validity assessment encompasses Kaiser-Meyer-Olkin (KMO), Bartlett's Test, and factor loadings. In Table 6, the KMO value at 0.956, signalling data suitability for factor analysis, as endorsed by Bennett et al. (2023) and Nkansah (2011). Additionally, the significance value of Bartlett's Test is remarkably less than 0.001, well below the conventional significance threshold of 0.05, thus confirming the data's suitability for analysis, following the recommendations of Bennett et al. (2023) and Taherdoost et al. (2022). Furthermore, the factor loadings in Table 5 distinctly reveal the presence of six separate factors, each with factor loadings exceeding 0.5. Consequently, there are no apparent concerns regarding discriminant validity, further strengthening the validity of these constructs, as corroborated by Napitupulu et al. (2017) and Arifin & Yusoff (2016).

Table 5. Result of Cronbach's Alpha and Factor Loadings

Constructs	**Items**	**Factor Loadings**	**Cronbach's Alpha (α)**
Perceived Usefulness (PU)	PU1	.787	.924
	PU2	.786	
	PU3	.864	
	PU4	.828	
	PU5	.865	
Perceived Ease of Use (PEU)	PEU1	.890	.944
	PEU2	.872	
	PEU3	.944	
	PEU4	.928	
	PEU5	.906	
Perceived Enjoyment (PE)	PE1	.700	.925
	PE2	.624	
	PE3	.641	
	PE4	.673	
Perceived Anthropomorphism (PA)	PA1	.923	.920
	PA2	.763	
	PA3	.846	
	PA4	.917	
	PA5	.865	
Perceived Intelligence (PI)	PI1	.554	.916
	PI2	.697	
	PI3	.855	
	PI4	.838	
	PI5	.831	
	PI6	.937	
	PI7	.854	
Continuance Intention to Use (CI)	CI1	.946	.880
	CI2	.890	
	CI3	.720	
	CI4	.798	

In this study, five direct hypotheses (H1, H2, H3, H4, and H5) were formulated to examine relationships between constructs. The analysis focuses on evaluating the significance, denoted by p-values (Bennett et al., 2023), and the t-values (Koç & Erkan Can, 2023). According to the findings presented in Table 6, the variation in continuance intention to use (CI) can be largely explained, approximately 44.7%, by the combined influence of five independent variables: perceived usefulness (PU), perceived ease of use (PEU), perceived enjoyment (PE), perceived anthropomorphism (PA), and perceived intelligence (PI).

It was evident that there were statistically significant, direct, positive relationships between PU and CI, PEU and CI, PE and CI, and PI and CI. These relationships were supported by results showing p-values below 0.05 and t-values exceeding 1.96, indicating their statistical robustness and significance. In contrast, the relationship between PA and CI did not exhibit statistical significance, as indicated by a p-value exceeding 0.05 and a t-value falling below 1.96.

Table 6. Summary for PU + PEU + PE + PA + PI → CI

Model	R-Square	Std. Error of the Estimate	Unstandardized Coefficients		Standardized Coefficients	t	Sig	Test result
			B	Std. Error	Beta			
Model Summary	.447	3.4410						
T_PU			.153	.037	.221	4.153	<.001	Supported
T_PEU			.154	.041	.235	3.755	<.001	Supported
T_PE			.113	.055	.136	2.068	.039	Supported
T_PA			-.029	.034	-.044	-.867	.386	Unsupported
T_PI			.143	.028	.248	5.155	<.001	Supported

Note: T_CI=Total Continuance Intention to Use, T_PU=Total Perceived Usefulness, T_PEU=Total Perceived Ease of Use, T_PE= Total Perceived Enjoyment, T_PA=Total Perceived Anthropomorphism, T_PI=Total Perceived Intelligence

In this research, age serves as a moderating variable, prompting the division of the sample into two groups: “young” and “old.” This classification aligns with Liébana-Cabanillas et al.’s (2021) study, where individuals with a median age of less than 35 were identified as “young” users (n=263), while those aged 35 and above were categorized as “old” users (n=135).

Moderated hypotheses are deemed valid when the t-value is ≥ 1.645, p-value ≤ 0.05, and no missing values fall within the confidence interval (LLCI to ULCI) (Sukri et al., 2023). R^2 is commonly used to assess predictive accuracy, but when few exogenous variables influence an endogenous latent variable, relying solely on R^2 can be problematic. Cohen’s effect size (f^2) serves as an alternative to assess the model, representing R^2 variations when excluding a specific construct (Karimi Mazidi et al., 2021).

In this research, five hypotheses (H6, H7, H8, H9, and H10) have been formulated to examine the moderating effect of age on relationships. There are 4 hypotheses supported: H1, H2, H3 and H5. While H4 is not supported.

This research makes a notable theoretical contribution to existing literature. Grounded in the Technology Acceptance Model (TAM) and the Extended Meta-UTAUT (Unified Theory of Acceptance and Use of Technology) framework, the empirical results clearly indicate that users' decisions to continue using AI-driven mobile banking applications are closely linked to their perceptions of usefulness, ease of use, enjoyment, and intelligence. Notably, this study highlights the crucial role of perceived intelligence in shaping users’ cognitive responses and their assessment of AI technology’s influence on their sustained usage intentions (Lee & Chen, 2022). Conversely, the findings suggest that perceived anthropomorphism has a relatively weaker impact on users' perceptions regarding their continued engagement with AI-enabled mobile banking applications.

Furthermore, this study probes the impact of age on responses associated with the ongoing commitment to using AI-powered mobile banking apps across diverse user demographics. In this regard, it expands upon the Technology Acceptance Model (TAM) and the Extended Meta-UTAUT framework by elucidating the moderating role played by cognitive factors and AI attributes in determining the continuation of usage. In summary, this research bridges a crucial gap by providing empirical evidence that uncovers the intricate relationships among cognitive factors, AI features, users' age, and the intent to continue using AI-enabled mobile banking apps. Consequently, it makes substantial theoretical contributions and implications for our understanding of users' experiences in terms of cognitive dimensions and functional aspects, ultimately influencing their continued intention to use mobile banking within AI-driven scenarios.

The current study carries significant practical ramifications deserving of thoughtful attention. Primarily, mobile banking software developers must exercise prudence in the construction of AI-infused mobile banking systems. These systems should deliver pertinent, reliable, tailored, accurate, and up-to-date information in an easily accessible format (Ashfaq et al., 2020), thereby nurturing a favourable disposition among users towards the adoption of AI-driven mobile banking apps (Belanche et al., 2019). To excel in delivering top-tier service quality, AI-powered mobile banking systems must tailor information to the unique needs of mobile banking users while staying attuned to current trends. This strategic approach aims to broaden the user base for AI-driven mobile banking applications, prompting banks to address customer concerns and elevate perceptions of AI systems (Ashfaq et al., 2020). To achieve this goal, it is imperative to educate customers about the advantages and profitability associated with using AI-powered mobile banking apps. This can be facilitated by enabling user engagement with robo-advisor platforms, even if their investments are minimal or non-existent. Alternatively, integrating conversational systems such as chatbots or digital assistants can enhance human-machine interactions and elevate interface interactivity (Belanche et al., 2019).

The research and development teams should contemplate the integration of AI technology to better harmonise with users' needs and objectives, reduce errors, and enhance dependability. The overarching objective is to imbue mobile banking apps development with heightened intelligence, thereby elevating efficiency and ensuring users can seamlessly accomplish their banking tasks (Lee & Chen, 2022). Simultaneously, within our progressively diverse society, user requirements are becoming increasingly multifaceted, thus underscoring the necessity for tailored services.

4. CONCLUSIONS AND SUGGESTIONS

This study acknowledges specific limitations that can guide future research efforts. First, survey samples for this study are exclusively from Malaysia, potentially limiting the broader applicability of the findings. Future research could replicate this study in different countries or regions to attain results of greater relevance. Second, several studies have suggested that affluent and highly educated individuals are more inclined to adopt and consistently use Internet banking services (Mattila et al., 2003; Polatoglu & Ekin, 2001). Future research could investigate whether income and education levels act as moderating factors, exploring whether the model behaves differently when applied to users with varying income and educational backgrounds

Finally, the study did not establish the significance of perceived anthropomorphism in relation to the intention to continue using mobile banking apps. While some research suggests that highly human-like systems may threaten users' human identity, alternative studies emphasise the role of perceived anthropomorphism in shaping users' determination to continue using such applications (Pelau et al., 2021; Balakrishnan et al., 2022). Conducting longitudinal research to explore the lasting effects of perceived anthropomorphism on users' resolve to continue using AI-enhanced mobile banking applications is advisable.

REFERENCES

Abdulquadri, A., Mogaji, E., Kieu, T. A., & Nguyen, N. P. (2021). Digital transformation in financial services provision: A Nigerian perspective to the adoption of chatbot. Journal of Enterprising Communities: People and Places in the Global Economy, 15(2), 258-281. https://doi-org.tarc.idm.oclc.org/10.1108/JEC-06-2020-0126

Alkhowaiter, W. A. (2022). Use and behavioural intention of m-payment in GCC countries: Extending meta-UTAUT with trust and Islamic religiosity. Journal of Innovation & Knowledge, 7(4), 100240. https://doi.org/10.1016/j.jik.2022.100240

Ambalov, I. A. (2021). An investigation of technology trust and habit in IT use continuance: a study of a social network. Journal of Systems and Information Technology, 23(1), 53-81. https://doi-org.tarc.idm.oclc.org/10.1108/JSIT-05-2019-0096

Andrade, C. (2020). Sample size and its importance in research. Indian Journal of Psychological Medicine, 42(1), 102-103. https://doi:10.4103/IJPSYM.IJPSYM_504_19

Arifin, W. N., & Yusoff, M. S. B. (2016). Confirmatory factor analysis of the Universiti Sains Malaysia emotional quotient inventory among medical students in Malaysia. Sage Open, 6(2), 2158244016650240. https://doi.org/10.1177/2158244016650240

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modelling the determinants of users' satisfaction and continuance intention of AI-powered service agents. Telematics and Informatics, 54, 101473. https://doi.org/10.1016/j.tele.2020.101473

Azeem, M., Ahmed, M., Haider, S., & Sajjad, M. (2021). Expanding competitive advantage through organizational culture, knowledge sharing and organizational innovation. Technology in Society, 66, 101635. https://doi.org/10.1016/j.techsoc.2021.101635

Baabdullah, A. M., Alalwan, A. A., Rana, N. P., Kizgin, H., & Patil, P. (2019). Consumer use of mobile banking (M-Banking) in Saudi Arabia: Towards an integrated model. International Journal of Information Management, 44, 38-52. https://doi.org/10.1016/j.ijinfomgt.2018.09.002

Balakrishnan, J., Abed, S. S., & Jones, P. (2022). The role of Meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services?. Technological Forecasting and Social Change, 180, 121692. https://doi.org/10.1016/j.techfore.2022.121692

Bartneck, C., Kulić, D., Croft, E., & Zoghbi, S. (2009). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. International Journal of Social Robotics, 1, 71-81. https://doi.org/10.1007/s12369-008-0001-3

Bassiouni, D. H., Hackley, C., & Meshreki, H. (2019). The integration of video games in family-life dynamics: an adapted technology acceptance model of family intention to consume video games. Information Technology & People, 32(6), 1376-1396. https://doi-org.tarc.idm.oclc.org/10.1108/ITP-11-2017-0375

Belanche, D., Casaló, L.V., & Flavián, C. (2019). Artificial intelligence in fintech: understanding robo-advisors adoption among customers. Industrial Management & Data

Systems, 119(7), 1411-1430. https://doi-org.tarc.idm.oclc.org/10.1108/IMDS-08-2018-0368

Bennett, K., Heritage, B., & Allen, P. (2023). SPSS Statistics: A Practical Guide 5th Edition. Cengage Learning Australia Pty Limited. https://research-repository.uwa.edu.au/en/publications/spss-statistics-a-practical-guide-5th-edition

Bergmann, M., Maçada, A. C. G., de Oliveira Santini, F., & Rasul, T. (2023). Continuance intention in financial technology: a framework and meta-analysis. International Journal of Bank Marketing, 41(4), 749-786. https://doi-org.tarc.idm.oclc.org/10.1108/IJBM-04-2022-0168

Bergur Thormundsson. (2022, Mar 17). Projected spending on artificial intelligence by industry group worldwide in 2020. Statista.
https://www.statista.com/statistics/940783/ai-spending-by-industry-group/

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. MIS Quarterly, 351-370. https://doi.org/10.2307/3250921

Blut, M., Wang, C., Wünderlich, N. V., & Brock, C. (2021). Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI. Journal of the Academy of Marketing Science, 49, 632-658. https://doi.org/10.1007/s11747-020-00762-y

Borau, S., Otterbring, T., Laporte, S., & Fosso Wamba, S. (2021). The most human bot: Female gendering increases humanness perceptions of bots and acceptance of AI. Psychology & Marketing, 38(7), 1052-1068. https://doi.org/10.1002/mar.21480

Buckley, R. P., Zetzsche, D. A., Arner, D. W., & Tang, B. W. (2021, April). Regulating artificial intelligence in finance: Putting the human in the loop. Sydney Law Review, The, 43(1), 43-81.

Cao, Y., Qin, X., Li, J., Long, Q., & Hu, B. (2022). Exploring seniors' continuance intention to use mobile social network sites in China: a cognitive-affective-conative model. Universal Access in the Information Society, 21, 1-22. https://doi.org/10.1007/s10209-020-00762-3

Chandler, J., & Schwarz, N. (2010). Use does not wear ragged the fabric of friendship: thinking of objects as alive makes people less willing to replace them. Journal of Consumer Psychology, 20(2), 138-145. https://doi.org/10.1016/j.jcps.2009.12.008

Chaouali, W., Ben Yahia, I., Lunardo, R., & Triki, A. (2019). Reconsidering the "what is beautiful is good" effect: When and how design aesthetics affect intentions towards mobile banking applications. International Journal of Bank Marketing, 37(7), 1525-1546. https://doi-org.tarc.idm.oclc.org/10.1108/IJBM-12-2018-0337

Chawla, D., & Joshi, H. (2020). The moderating role of gender and age in the adoption of mobile wallet. Foresight, 22(4), 483-504. https://doi-org.tarc.idm.oclc.org/10.1108/FS-11-2019-0094

Chen, C. Y., Yang, H. C. P., Chen, C. W., & Chen, T. H. (2008). Diagnosing and revising logistic regression models: effect on internal solitary wave propagation. Engineering Computations, 25(2), 121-139. https://doi-org.tarc.idm.oclc.org/10.1108/02644400810855940

Choi, K., Wang, Y., & Sparks, B. (2019). Travel app users' continued use intentions: it's a matter of value and trust. Journal of Travel & Tourism Marketing, 36(1), 131-143. https://doi:10.1080/10548408.2018.1505580

Chung, J. E., Park, N., Wang, H., Fulk, J., & McLaughlin, M. (2010). Age differences in perceptions of online community participation among non-users: An extension of the Technology Acceptance Model. Computers in Human Behavior, 26(6), 1674-1684. https://doi.org/10.1016/j.chb.2010.06.016

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. Journal of Business Research, 117, 587-595. https://doi.org/10.1016/j.jbusres.2018.10.004

Danyali, A. A. (2018). Factors influencing customers' change of behaviors from online banking to mobile banking in Tejarat Bank, Iran. Journal of Organizational Change Management, 31(6), 1226-1233. https://doi-org.tarc.idm.oclc.org/10.1108/JOCM-07-2017-0269

De Winter, J. C., Gosling, S. D., & Potter, J. (2016). Comparing the Pearson and Spearman correlation coefficients across distributions and sample sizes: A tutorial using simulations and empirical data. Psychological Methods, 21(3), 273. https://doi.org/10.1037/met0000079

Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services–the effect of technology readiness and awareness. Journal of Service Management, 33(2), 293-320. https://doi-org.tarc.idm.oclc.org/10.1108/JOSM-10-2020-0378

Gong, X., Liu, Z., Zheng, X., & Wu, T. (2018). Why are experienced users of WeChat likely to continue using the app?. Asia Pacific Journal of Marketing and Logistics, 30(4), 1013-1039. https://doi-org.tarc.idm.oclc.org/10.1108/APJML-10-2017-0246

Grazzini, L., Viglia, G., & Nunan, D. (2023). Dashed expectations in service experiences. Effects of robots human-likeness on customers' responses. European Journal of Marketing, 57(4), 957-986. https://doi-org.tarc.idm.oclc.org/10.1108/EJM-03-2021-0220

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. Journal of Marketing Theory and Practice, 19(2), 139-152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J.F., Hult, G.T.M., Ringle, C.M., & Sarstedt, M. (2016). A primer on partial least squares structural equation modeling (PLS-SEM). SAGE Publications. https://www.google.com.my/books/edition/A_Primer_on_Partial_Least_Squares_Struct/JDWmCwAAQBAJ?hl=en&gbpv=1

Hassan, H. E., & Wood, V. R. (2020). Does country culture influence consumers' perceptions toward mobile banking? A comparison between Egypt and the United States. Telematics and Informatics, 46, 101312. https://doi.org/10.1016/j.tele.2019.101312

Hentzen, J. K., Hoffmann, A., Dolan, R., & Pala, E. (2022). Artificial intelligence in customer-facing financial services: a systematic literature review and agenda for future research. International Journal of Bank Marketing, 40(6), 1299-1336. https://doi-org.tarc.idm.oclc.org/10.1108/IJBM-09-2021-0417

Hidayat-ur-Rehman, I., Ahmad, A., Khan, M. N., & Mokhtar, S. A. (2021). Investigating mobile banking continuance intention: a mixed-methods approach. Mobile Information System, 2021, 1-17. https://doi.org/10.1155/2021/9994990

Hoque, R., & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model. International Journal of Medical Informatics, 101, 75-84. https://doi.org/10.1016/j.ijmedinf.2017.02.002

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

Iancu, I., & Iancu, B. (2020). Designing mobile technology for elderly. A theoretical overview. Technological Forecasting and Social Change, 155, 119977. https://doi.org/10.1016/j.techfore.2020.119977

Illum, S. F., Ivanov, S. H., & Liang, Y. (2010). Using virtual communities in tourism research. Tourism Management, 31(3),335-340. https://doi.org/10.1016/j.tourman.2009.03.012

Jo, H. (2023). Understanding the key antecedents of users' continuance intention in the context of smart factory. Technology Analysis & Strategic Management, 35(2), 153-166. https://doi.org/10.1080/09537325.2021.1970130

Kamide, H., Kawabe, K., Shigemi, S., & Arai, T. (2013). Development of a psychological scale for general impressions of humanoid. Advanced Robotics, 27(1), 3-17. https://doi.org/10.1080/01691864.2013.751159

Karimi Mazidi, A., Rahimnia, F., Mortazavi, S., & Lagzian, M. (2021). Cyberloafing in public sector of developing countries: job embeddedness as a context. Personnel Review, 50(7/8), 1705-1738. https://doi-org.tarc.idm.oclc.org/10.1108/PR-01-2020-0026

Khalilzadeh, J., & Tasci, A. D. (2017). Large sample size, significance level, and the effect size: Solutions to perils of using big data for academic research. Tourism Management, 62, 89-96. https://doi.org/10.1016/j.tourman.2017.03.026

Kim, H., So, K. K. F., & Wirtz, J. (2022). Service robots: Applying social exchange theory to better understand human–robot interactions. Tourism Management, 92, 104537. https://doi.org/10.1016/j.tourman.2022.104537

Koç, D. L., & Erkan Can, M. (2023). Reference evapotranspiration estimate with missing climatic data and multiple linear regression models. PeerJ, 11, e15252. https://doi.org/10.7717/peerj.15252

Königstorfer, F., & Thalmann, S. (2020). Applications of Artificial Intelligence in commercial banks–A research agenda for behavioral finance. Journal of Behavioral and Experimental Finance, 27, 100352. https://doi.org/10.1016/j.jbef.2020.100352

Kwateng, K. O., Atiemo, K. A. O., & Appiah, C. (2019). Acceptance and use of mobile banking: an application of UTAUT2. Journal of Enterprise Information Management, 32(1), 118-151. https://doi-org.tarc.idm.oclc.org/10.1108/JEIM-03-2018-0055

Larson, K. (2020). Serious games and gamification in the corporate training environment: A literature review. TechTrends, 64(2), 319-328. https://doi.org/10.1007/s11528-019-00446-7

Lee, J. C., & Chen, X. (2022). Exploring users' adoption intentions in the evolution of artificial intelligence mobile banking applications: the intelligent and anthropomorphic perspectives. International Journal of Bank Marketing, 40(4), 631-658. https://doi-org.tarc.idm.oclc.org/10.1108/IJBM-08-2021-0394

Lee, J., Tang, Y., & Jiang, S. (2023). Understanding continuance intention of artificial intelligence (AI)-enabled mobile banking applications: An extension of AI characteristics to an expectation confirmation model. Humanities & Social Sciences Communications, 10(1), 333. https://doi.org/10.1057/s41599-023-01845-1

Letheren, K., Kuhn, K. A. L., Lings, I., & Pope, N. K. L. (2016). Individual difference factors related to anthropomorphic tendency. European Journal of Marketing, 50(5/6), 973-1002. https://doi-org.tarc.idm.oclc.org/10.1108/EJM-05-2014-0291

Liébana-Cabanillas, F., Singh, N., Kalinic, Z., & Carvajal-Trujillo, E. (2021). Examining the determinants of continuance intention to use and the moderating effect of the gender and age of users of NFC mobile payments: A multi-analytical approach. Information Technology and Management, 22, 133-161. https://doi.org/10.1007/s10799-021-00328-6

Lin, R. R., & Lee, J. C. (2023). The supports provided by artificial intelligence to continuous usage intention of mobile banking: evidence from China. Aslib Journal of Information Management, 2050-3806. https://doi-org.tarc.idm.oclc.org/10.1108/AJIM-07-2022-0337

Lin, X., Featherman, M., & Sarker, S. (2017). Understanding factors affecting users' social networking site continuance: A gender difference perspective. Information & Management, 54(3), 383-395. https://doi.org/10.1016/j.im.2016.09.004

Liu, Q., Liu, Y., Zhang, C., An, Z., & Zhao, P. (2021). Elderly mobility during the COVID-19 pandemic: A qualitative exploration in Kunming, China. Journal of Transport Geography, 96, 103176.

Liu, X., He, X., Wang, M., & Shen, H. (2022). What influences patients' continuance intention to use AI-powered service robots at hospitals? The role of individual characteristics. Technology in Society, 70, 101996. https://doi.org/10.1016/j.techsoc.2022.101996

Makanyeza, C. (2017). Determinants of consumers' intention to adopt mobile banking services in Zimbabwe. International Journal of Bank Marketing, 35(6), 997-1017. https://doi-org.tarc.idm.oclc.org/10.1108/IJBM-07-2016-0099

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

Mamun, M. R. A., Prybutok, V. R., Peak, D. A., Torres, R., & Pavur, R. J. (2023). The role of emotional attachment in IPA continuance intention: an emotional attachment model. Information Technology & People, 36(2), 867-894. https://doi-org.tarc.idm.oclc.org/10.1108/ITP-09-2020-0643

Mattila, M., Karjaluoto, H., & Pento, T. (2003). Internet banking adoption among mature customers: early majority or laggards?. Journal of Services Marketing, 17(5), 514-528. https://doi-org.tarc.idm.oclc.org/10.1108/08876040310486294

McLean, G., Osei-Frimpong, K., Al-Nabhani, K., & Marriott, H. (2020). Examining consumer attitudes towards retailers' m-commerce mobile applications–an initial adoption vs. continuous use perspective. Journal of Business Research, 106, 139-157. https://doi.org/10.1016/j.jbusres.2019.08.032

Mehra, A., Rajput, S., & Paul, J. (2022). Determinants of adoption of latest version smartphones: Theory and evidence. Technological Forecasting and Social Change, 175,121410. https://doi.org/10.1016/j.techfore.2021.121410

Modiba, M. (2023). User perception on the utilisation of artificial intelligence for the management of records at the council for scientific and industrial research. Collection and Curation, 42(3), 81-87. https://doi-org.tarc.idm.oclc.org/10.1108/CC-11-2021-0033

Montes, G. A., & Goertzel, B. (2019). Distributed, decentralized, and democratized artificial intelligence. Technological Forecasting and Social Change, 141, 354-358. https://doi.org/10.1016/j.techfore.2018.11.010

Morris, M. G., & Venkatesh, V. (2000). Age differences in technology adoption decisions: Implications for a changing work force. Personnel Psychology, 53(2), 375-403. https://doi.org/10.1111/j.1744-6570.2000.tb00206.x

Mostafa, R. B. (2020). Mobile banking service quality: a new avenue for customer value co-creation. International Journal of Bank Marketing, 38(5), 1107-1132. https://doi-org.tarc.idm.oclc.org/10.1108/IJBM-11-2019-0421

Moussawi, S., Koufaris, M., & Benbunan-Fich, R. (2021). How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents. Electronic Markets, 31, 343-364. https://doi.org/10.1007/s12525-020-00411-w

Napitupulu, D., Kadar, J. A., & Jati, R. K. (2017). Validity testing of technology acceptance model based on factor analysis approach. Indonesian Journal of Electrical Engineering and Computer Science, 5(3), 697-704. https://doi.org/10.11591/ijeecs.v5.i3.pp697-704

Naqvi, M., Li, S., Jiang, Y., & Naqvi, M. H. A. (2020). The rise of social networking sites: an empirical investigation applying demographic differences and the technology acceptance model. Asia Pacific Journal of Marketing and Logistics, 32(1), 232-252. https://doi-org.tarc.idm.oclc.org/10.1108/APJML-01-2019-0029

Nkansah, B. K. (2011). On the Kaiser-meier-Olkin's measure of sampling adequacy. Math. Theory Model, 8, 52-76. https://api.core.ac.uk/oai/oai:ojs.localhost:article/44386

Pan, W. T. (2010). Performing stock price prediction use of hybrid model. Chinese Management Studies, 4(1), 77-86. https://doi-org.tarc.idm.oclc.org/10.1108/17506141011033016

Pelau, C., Dabija, D. C., & 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, 122, 106855. https://doi.org/10.1016/j.chb.2021.106855

Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. International Journal of Contemporary Hospitality Management, 32(10), 3199-3226. https://doi-org.tarc.idm.oclc.org/10.1108/IJCHM-04-2020-0259