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Impacts of AI-integrated services and corporate reputation on digitalised banking recommendations: a view of goal-framing theory

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Abstract

Purpose – The convergence of banking operations with advanced technologies is beyond technical and signifies the shift toward customer-centric banking experiences enabled through strategic service delivery. To that end, this study investigates the effects of AI-integrated banking services and corporate reputation on customers' assessment and intention to recommend digitalised banking services (DBS). The study further examines the mediating role of DBS assessment and compares these relationships across customer groups distinguished by varying levels of financial literacy and attitudes toward promotional offers.

Design/methodology/approach – Drawing on goal-framing theory (GFT), this study employs partial least squares structural equation modelling (PLS-SEM) and multi-group analysis to analyse data collected from 758 DBS users. The model incorporates both service-level factors and individual-level characteristics, including financial knowledge and attitudes toward promotional offers.

Findings – The results reveal that AI-integrated services and corporate reputation significantly influence customers' assessment of DBS, exerting both direct and indirect effects on recommendation intention. The influence of AI-integrated services is fully mediated by DBS assessment. Multi-group analysis further shows that customers with low financial knowledge rely more on corporate reputation, whereas those with high promotion attitudes are more responsive to AI-integrated services.

Research limitations/implications – This study extends goal-framing theory to the context of AI-enabled banking by identifying the mediating mechanism of service assessment and exploring the moderating effects of customer traits.

Practical implications – The findings offer actionable insights for financial institutions and policymakers. Clearer AI-related guidelines and digital finance education strategies can empower underserved users. Inclusive service design and trust-building strategies can enhance engagement among diverse customer groups.

Originality/value – This study is among the first to jointly examine the effects of AI-enabled DBS design and corporate reputation on DBS recommendation intention while accounting for key customer characteristics.

Keywords Digitalised banking, AI integration, Corporate reputation, Service assessment, Intention to recommend, Financial knowledge, Attitudes towards promotions, Multi-group analysis

Paper type Research article

1. Introduction

Advancements in innovative financial technologies, particularly artificial intelligence (AI), have transformed banking services globally (Desiraju *et al.*, 2024; Ren, 2021). The growth of digitalised banking services (DBS) including app-based payments, chatbot-assisted services, and mobile platforms has reshaped customer behaviour and expectations (Chauhan, 2024; Dorfleitner *et al.*, 2021). These changes are evident in South Korea, where mobile banking transactions grew by 19.2% in 2024 to reach 19.1 million, now accounting for 86.9% of all

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online banking activities. Internet-only banks have expanded rapidly, with mobile transactions increasing 2.7 times since 2019, making up 25.7% of total transactions (Han, 2024; The Bank of Korea, 2024).

The banking industry is now characterised by the coexistence of traditional financial structures with AI-integrated services (Shaikh *et al.*, 2023). New players, such as fintech and app-only banks have adopted customer-centric strategies, intensifying competition with legacy institutions (Mogaji, 2023). As banking moves toward hyper-personalised and real-time services, integrating AI is no longer a competitive advantage but a necessity (Windasari *et al.*, 2022). However, this transformation also brings new challenges (particularly around customer trust, confidence, and behavioural intentions)highlighting the need to examine technical functionality and intangible factors such as corporate reputation (Sharma and Joshi, 2022; Zhao *et al.*, 2023).

Reputation reflects customer perceptions of a bank's stability, credibility, and quality of service (Gerrard and Cunningham, 2004). While its role in traditional banking is well documented, limited research has explored how reputation influences customer assessments and recommendation behaviours in the context of AI-enhanced DBS (Hornuf *et al.*, 2020). At the same time, customer individual traits (i.e. financial knowledge and attitudes toward promotions) further shape their evaluations. Customers with lower financial literacy tend to rely on AI-powered tools for convenience (Koskelainen *et al.*, 2023), while those with positive promotional attitudes respond more favourably to digital incentives (Jiang *et al.*, 2021; Windasari *et al.*, 2022). Despite their growing importance, few studies have examined how these traits moderate the effects of service characteristics in digital banking environments (Aziz and Naima, 2021; Ravikumar *et al.*, 2022).

Accordingly, this study investigates (1) the potential synergy between AI integration and corporate reputation in shaping customer evaluations and recommendation intentions and (2) how these relationships may vary depending on customer-level traits, such as financial knowledge and attitudes toward promotions. Based on goal-framing theory (GFT), the study proposes a conceptual model in which customers' DBS assessments mediate the effects of service attributes on behavioural outcomes. Goal (gain) orientation, rooted in GFT, examines how an individual's thoughts are connected to their goals. Identifying the key drivers of customers' gain motivation during DBS engagement can advance academic and managerial understanding of their sensitivities and expectations regarding DBS benefits. We employ partial least squares structural equation modelling (PLS-SEM) and multi-group analysis on a dataset of 758 DBS users in South Korea to examine these relationships. The findings aim to bridge theoretical gaps in understanding the synergy between technology and reputation, offering practical implications for personalised and inclusive digital banking strategies.

The remainder of the paper is structured as follows: Section 2 presents the theoretical background, and Section 3 introduces the hypotheses. Sections 4 and 5 describe the methodology and results. Section 6 discusses the implications, and Section 7 concludes with limitations and directions for future research.

2. Literature review and theoretical background

2.1 Digitalised banking service: AI technology and corporate reputation

DBS reflects traditional banking operations' convergence with advanced technologies such as AI. These services redefine conventional banking models and are increasingly central to financial institutions' strategic planning (Desiraju *et al.*, 2024; Ren, 2021). DBS encompasses AI-driven operational systems, personalised financial tools, and mobile-first platforms developed by traditional institutions and fintech disruptors (Barone *et al.*, 2024; Dorfleitner *et al.*, 2021). The convergence goes beyond technical aspects, representing a move toward customer-centric banking, emphasising usability and trust (Shaikh *et al.*, 2023).

2.1.1 Role of AI integration in the digital banking experience. AI integration offers efficiency, security, and scalability in digital finance. Studies show that AI enhances operational speed and precision while enabling personalised services such as chatbots, virtual assistants, and fraud detection (Königstorfer and Thalmann, 2020; Luo *et al.*, 2020). AI integration approaches reduce manual errors and improve user experience by adapting to customer inquiries and delivering consistent service (Lin *et al.*, 2020; Zhu *et al.*, 2022). However, despite the technological benefits, customer perception remains inconsistent (Barone *et al.*, 2024; Hamakhan and Taha, 2020; Nishant *et al.*, 2020; Urbani *et al.*, 2024). For instance, Wang *et al.* (2022) noted that users' trust and behavioural adaptation to AI systems often lag due to the complexity and perceived impersonality of such services. This observation aligns with the findings of Shaikh *et al.* (2023), who highlighted that DBS requires coordination across diverse platforms and actors, thereby complicating the impact of AI.

2.1.2 Role of corporate reputation in the digital banking experience. Corporate reputation is a cognitive shortcut in customers' evaluation of digital financial platforms. It encompasses perceived stability, service quality, and ethical standards. In environments with limited information or new technologies, reputation reduces uncertainty and builds initial trust (Gerrard and Cunningham, 2004). Prior research shows that reputation affects both satisfaction and post-purchase behaviours, such as switching and recommendations (Andreassen and Lindestad, 1998; Sharma and Joshi, 2022). Recent studies suggest that reputation is particularly salient in digitally native environments, where customers may lack other tangible indicators of reliability (Bugandwa *et al.*, 2021; Nguyen *et al.*, 2022).

2.1.3 Mediating role of digital banking assessment. Service assessment reflects how customers evaluate the usefulness, accessibility, and reliability of DBS. It also acts as a mediating construct that links service characteristics with behavioural outcomes (Andreassen and Lindestad, 1998; Payne *et al.*, 2021). For example, Barone *et al.* (2024) suggest that customers may view AI features as distinct technological utilities rather than integrated service experiences unless mediated by positive evaluations. Similarly, Mogaji and Nguyen (2024) stress that reputation alone does not drive recommendation unless users positively assess their overall service experience. Thus, DBS assessment is an outcome and a mechanism through which service features shape customer intention.

2.2 Assessment-based recommendation intention of DBS

The intention to recommend a DBS is influenced by perceived value, satisfaction, and service performance (Cheng *et al.*, 2024). Laukkanen (2016) identified assessment as a key predictor of adoption and recommendation, particularly in digital contexts. The DBS assessment measures comfort with AI-driven features, including automated advice, chatbots, and transparency (Payne *et al.*, 2021). Positive assessment translates into behavioural intentions such as loyalty and word-of-mouth (Ghadiridehkordi *et al.*, 2024; Sheth *et al.*, 2022).

2.2.1 Customer experience-based assessment and goal-framing theory perspective. Goal (gain) orientation is rooted in GFT, which examines how individuals' thoughts are connected with their goals (Lindenberg and Steg, 2007). GFT proposes that an individual's perceptions and actions are founded on hedonic, gain, and normative goals (Bonhi *et al.*, 2024). This study focuses on the goal of gaining, which individuals form to protect and develop their resources (Shah *et al.*, 2024). Gaining motivation effectively encourages users to make decisions that maximise their benefits while protecting and improving their resources with minimal cost (Jain and Rathi, 2023). In this context, the banking industry has unique characteristics, as customers have distinct sensitivities and expectations regarding the benefits of DBS. Therefore, including the gain motivation perspective helps better understand how a customer's focal goal (i.e. choosing a DBS for asset management) becomes stronger or weaker depending on how they process the DBS information.

2.2.2 Financial knowledge. Financial knowledge enables users to navigate digital platforms effectively and assess the credibility of services (Bunnell *et al.*, 2021; Okamoto and Komamura, 2021). Individuals with higher financial literacy are more likely to adopt complex financial tools, make rational choices, and detect risks (Babajide *et al.*, 2021). Conversely, users with limited financial knowledge tend to rely on simple cues, such as brand recognition or user interface, when making decisions (Aziz and Naima, 2021; Koskelainen *et al.*, 2023). Financial knowledge thus may affect how customers interpret and respond to AI and reputation-based signals in DBS.

2.2.3 Attitudes towards promotions. Attitudes towards promotions reflect customers' responsiveness to marketing incentives, such as discounts or cashback. These attitudes affect perception and behavioural responses to DBS. Customers open to promotions or engagements tend to perceive AI-enhanced services more positively, viewing them as value-enhancing (Bapat, 2021; Windasari *et al.*, 2022). Research suggests that promotions can either enhance or dilute the DBS experience, depending on their alignment with customer expectations and ability to motivate (Indriyarti *et al.*, 2023; Shah *et al.*, 2024). Thus, promotional attitudes interact with service features in shaping DBS assessment and recommendation intention.

3. Hypotheses development

3.1 AI integration and corporate reputation's impact on customer assessment and behavioural intention

AI and algorithm-based interactions have driven the DBS transformation to offer features such as voice or text-based support (Kautish *et al.*, 2023; Luo *et al.*, 2020) and customised investment decisions (Ren, 2021). This shift highlights the move towards customer-centric and relationship-driven marketing approaches to provide more personalised banking experiences (Ooi *et al.*, 2023). Although fears of data breaches and resistance to AI due to its potential malicious use can lead to negative perceptions (Huang *et al.*, 2021), recent advancements in cloud computing and big data have highlighted the benefits of AI applications (Casheekar *et al.*, 2024).

H1. The use of AI-integrated banking services leads to higher customer DBS assessments.

Corporate reputation is critical in creating sustainable competitive advantages and can influence banks' customer acquisition and transaction processes (Zhao *et al.*, 2023). It significantly impacts customers' loyalty and intention to engage with DBS (Nguyen *et al.*, 2022). Brand positioning strategies by various bank types (traditional, fintech, neo banks) play a role in influencing customer perceptions (Mogaji and Nguyen, 2024; Ooi *et al.*, 2023).

H2. Corporate reputation leads to higher customer DBS assessments.

Customers share experiences with AI-integrated services to enhance trust and reduce uncertainty, impacting their WOM and recommendation behaviour (Heinberg *et al.*, 2018; Oghazi *et al.*, 2021). As digital transformations of retail services or mobile channels have been persistently regarded in parallel with digitalised services, the banking service with high AI embeddedness can potentially lead to customers' behavioural outcomes (Candiwan and Annikmah, 2024). AI chatbots and embedded AI functions improve navigation and personalised recommendations (Kautish *et al.*, 2023), while perceived convenience affects recommendation intentions (Wasan, 2018).

H3. Using AI-integrated banking services leads to higher customer intention to recommend DBS.

Corporate reputation or branding directly impacts customer recommendation behaviour, especially in digital contexts (Nguyen *et al.*, 2022). This relationship is influenced by various factors, such as perceived brand localness and foreignness, which significantly affect brand love and perceived coolness in digital retail banking (Safeer and Nazir, 2024). Furthermore, brand familiarity enhances brand image for both local and foreign digital retail banks (Garzaro *et al.*, 2020). Emotional attachment to the bank brand fosters loyalty and indirectly strengthens it through psychological engagement with digital service platforms (Levy, 2022). A positive corporate reputation also increases bank trust and its subsequent effect on loyalty (Sharma and Joshi, 2022).

H4. Corporate reputation leads to higher customer intention to recommend DBS.

Digital transformation demands innovation in engaging customer experiences (Ooi *et al.*, 2023). For example, digital financial service experiences are emphasised as an essential service feature as the customer experience has become a source of competitive advantage (Bapat, 2021). Personalisation and human interaction remain central to customer evaluation (Sheth *et al.*, 2022), and the assessment of internet-only banking varies across generational segments (Park *et al.*, 2024). Positive banking experiences influence the likelihood of recommendation (Barone *et al.*, 2024; Ghadiridehkordi *et al.*, 2024).

H5. DBS assessment leads to higher customer intention to recommend DBS.

While AI features and corporate reputation directly influence recommendation intention, they may also do so indirectly through DBS assessment. Prior research suggests that perceived ease, personalisation, and cognitive comfort, reflected in DBS assessments, can shape behavioural responses such as willingness to recommend (Andreassen and Lindestad, 1998; Payne *et al.*, 2021). Barone *et al.* (2024) further argue that users may perceive AI as a distinct technological value only when it is mediated by positive assessment of the service experience. Similarly, Mogaji and Nguyen (2024) demonstrate that corporate reputation alone cannot drive recommendations unless supported through service satisfaction.

H5a. DBS assessment mediates the relationship between AI-integrated banking services and the intention to recommend DBS.

H5b. DBS assessment mediates the relationship between corporate reputation and intention to recommend DBS.

3.2 Customers' financial knowledge and attitudes towards promotions

Customer-specific traits such as financial literacy and promotional orientation may influence how individuals interpret and respond to AI-integrated services and corporate reputation. Financial knowledge affects users' ability to process complex digital service features and assess value propositions. Customers with greater financial understanding are more likely to critically evaluate online and mobile banking tools (Lyons and Kass-Hanna, 2021; Morgan and Trinh, 2019), while those with lower financial knowledge may rely more on brand signals or promotional cues to inform their decisions. Studies show that financially literate customers evaluate DBS based on service depth and reliability, whereas others focus on accessibility and interface simplicity. Thus, customer responses to DBS may vary significantly depending on their level of financial knowledge. Lower financial knowledge can reduce trust and service usage, especially during crises (Cheng *et al.*, 2024; Sharma, 2021). Financial knowledge also influences customers' perception of DBS trustworthiness (Koskelainen *et al.*, 2023; Kumar *et al.*, 2023).

H6a. The positive effect of AI-integrated banking services on customer DBS assessment is higher for customers with lower financial knowledge.

H6b. The positive effect of AI-integrated banking services on customers' intention to recommend DBS is higher for customers with lower high financial knowledge.

H6c. The positive effect of corporate reputation on customer DBS assessment is higher for customers with lower financial knowledge.

H6d. The positive effect of corporate reputation on customers' intention to recommend DBS is lower for customers with lower financial knowledge.

DBS providers often use monetary or non-monetary promotions to encourage adoption and loyalty, but customers' attitudes toward these tactics vary. Some customers are motivated by economic benefits, while others respond to emotional or symbolic value (Jiang *et al.*, 2021; Nayal and Pandey, 2022). Individuals with favourable attitudes toward promotions tend to view them as enhancing service value and legitimacy, particularly when these align with perceived personal benefits and expectations (Indriyarti *et al.*, 2023; Iranmanesh *et al.*, 2017). When promotion aligns with customers' motivations and is perceived as trustworthy, it may amplify their assessment and recommendation intention for DBS. These findings suggest that the psychological orientation toward promotional stimuli significantly affects how customers evaluate digitally delivered services (Chauhan, 2024; Windasari *et al.*, 2022).

H7a. The positive effect of AI-integrated banking services on customer DBS assessment is higher for customers with positive attitudes towards promotion.

H7b. The positive effect of AI-integrated banking services on customers' intention to recommend DBS is higher for customers with positive attitudes towards promotion.

H7c. The positive effect of corporate reputation on customer DBS assessment is higher for customers with positive attitudes towards promotion.

H7d. The positive effect of corporate reputation on customers' intention to recommend DBS is higher for customers with positive attitudes towards promotion.

Figure 1 represents the relationship between all hypotheses discussed below.

4. Method and analysis

4.1 Data collection and non-response bias

To examine consumers' multifaceted experiences of DBS, a survey of 758 digital banking consumer panels was conducted. The sampling method was employed to develop a measurement model, and the survey was conducted using a global marketing firm approved by the Online Privacy Association's privacy certification system and monitored by the Korea Communications Commission and the Ministry of Patriots and Veterans Affairs. This technique prevented the falsification of participants' identities and ensured their data privacy

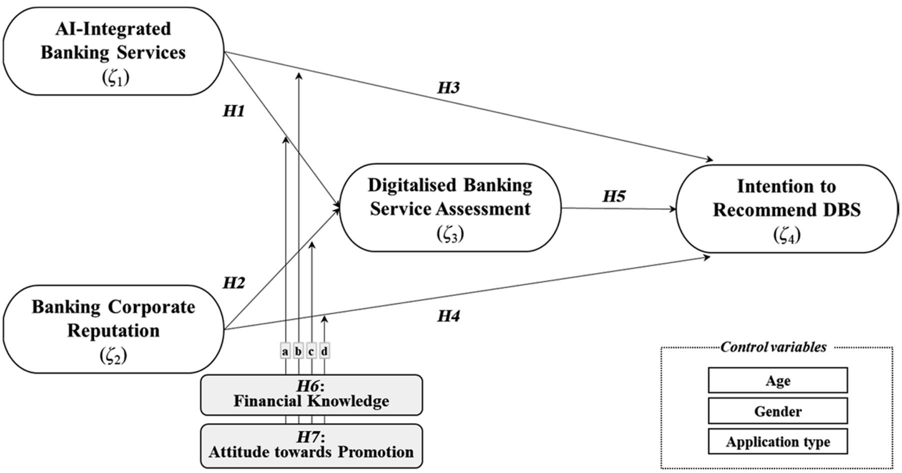

Figure 1. Hypothesised model of a digitalised banking service experience-based assessment. Source: Authors' own creation

and security. The participants' experience with DBS was screened using the following criteria: (1) has experienced AI-integrated banking services (e.g. chatbot-enabled account management); (2) has utilised DBS as a primary or secondary financial service. Non-response bias was assessed to ensure no significant difference between the first 25% and the last 25% of participants. The two groups revealed no significant differences in the study constructs or participant demographics ($p > 0.05$).

This study used a priority method (Shaikh *et al.*, 2023), ensuring that neither the research model nor the study objective was disclosed to participants and that the sequence of the survey items was randomised. This process attempted to limit common method variance by guaranteeing that the participants could not identify the dependent and independent variables.

4.2 Analytical method

The analysis was based on PLS-SEM, a suitable analytic tool for validating relationships among latent variables based on observed constructs (Hair *et al.*, 2019). Using a factor analysis, PLS-SEM increases the explanatory power of latent variables on the dependent variables (Dash and Paul, 2021). Thus, this study examines the hypothesised model and the association between latent variables using SmartPLS 4.

4.3 Variables

This study adopts various observed questions previously developed as a measurement model using a Likert scale (1 = strongly disagree, 7 = strongly agree). The AI integration in banking services measures the degree to which the consumer perceives the AI integration within services such as marketing, infrastructure, and financial products and services (Cao and Zhang, 2011). Corporate reputation is reflected by the degree to which consumers perceive the service provider as providing quick, friendly, and well-respected reputable services (Heinberg *et al.*, 2018; Oghazi *et al.*, 2021). DBS assessments are measured using consumers' comfort in using AI-integrated financial services such as automated voice and chat interactions and personalised investments developed through AI integration (Payne *et al.*, 2021). Lastly, consumer behavioural intention is the likelihood of engaging in subsequent action, such as recommending the service to friends or families (Hsieh and Lee, 2021).

4.4 Respondents' profile

Table 1 describes the demographic characteristics of the respondents. Regarding gender, there were 386 (50.92%) females. The age groups were uniformly distributed across 20s, 30s, 40s, and 50s with 24.80%, 26.65%, 23.75%, and 24.80% respectively. For monthly banking transaction frequency, more than half of the consumers engaged in <20 transactions (51.06%) and had transaction values of less than 100 USD (73.35%). These demographic variables are tested as control variables to examine potential confounding effects.

To test for potential confounding effects based on socio-demographic background, gender, age group, and application types are examined (Table 2). The control variables' testing results (age, gender, and application type) on the latent variables (assessment, integration, recommendation, and reputation) indicate limited significant impacts. Specifically, age did not have a statistically significant effect on any latent variables, with p-values exceeding 0.05 in all cases (e.g. assessment: $p = 0.098$; integration: $p = 0.360$). Similarly, gender demonstrated no significant relationship with latent variables (e.g. assessment: $p = 0.837$; integration: $p = 0.107$). However, application type had a significant negative effect on assessment ($p = 0.004$) and a significant positive effect on reputation ($p = 0.017$), while its impact on integration ($p = 0.791$) and recommendation ($p = 0.275$) was non-significant. Although application type had a notable effect on certain aspects, this is well related to the hypothesised impact of corporate reputation, which is related to the actual application type. Overall, the findings suggest that most control variables did not influence the latent constructs, which warrants further investigation into their roles.

Table 1. Participants' demographic characteristics ($N = 758$)

Variable	Characteristic	*n*	%
Gender	Male	372	49.08
	Female	386	50.92
Age group (years)	20s (20–29)	188	24.80
	30s (30–39)	202	26.65
	40s (40–49)	180	23.75
	50s (50–59)	188	24.80
No. of monthly banking transactions	Less than 20 transactions	387	51.06
	20–50	271	35.75
	21–70	60	7.92
	71–100	18	2.37
	More than 100 transactions	22	2.90
Monthly transaction value	Less than USD 100	556	73.35
	USD 101–300	143	18.87
	USD 301–500	27	3.56
	USD 501–1,000	22	2.90
	More than USD 1,000	10	1.32
Experience using AI-integrated banking services	Loan and lending services	293	38.65
	Payment and billing	237	31.27
	Personal finance and asset management	176	23.22
	Transfer	39	5.15
	Blockchain and cryptocurrency	9	1.19
	Market data information	3	0.40
	Security technology	1	0.12

Source(s): Authors' own creation

Table 2. Control variable statistics

	Mean	SD	*T*-statistics	*p*-value
Age				
Assessment	0.044	0.027	1.655	0.098
Integration	0.032	0.035	0.915	0.360
Recommendation	−0.006	0.025	0.215	0.830
Reputation	−0.011	0.036	0.295	0.768
Gender				
Assessment	0.012	0.057	0.206	0.837
Integration	0.117	0.073	1.610	0.107
Recommendation	−0.022	0.053	0.416	0.677
Reputation	0.004	0.074	0.063	0.950
Application type				
Assessment	−0.084	0.029	2.853	0.004
Integration	−0.009	0.036	0.265	0.791
Recommendation	0.028	0.026	1.093	0.275
Reputation	0.092	0.038	2.398	0.017

Source(s): Authors' own creation

4.5 Measurement model validity

This study used a two-step approach (Hair *et al.*, 2020; Shaikh *et al.*, 2023) to evaluate the measurement model's four constructs and 17 indicators. The factor loadings, item reliability, convergence, and discriminant validity were assessed against the thresholds (Table 3). All

Table 3. Constructs, indicators, and factor loadings

Construct	Indicator		Mean	SD	FL
AI-integrated banking services (ζ_1)	Reference:	Cao and Zhang (2011)			
	ζ_{11}	This DBS integrates AI-embedded marketing for comprehensive financial services	4.83	1.01	0.88
	ζ_{12}	This DBS integrates IT infrastructure with resources to enable comprehensive AI-integrated financial services	4.83	1.00	0.90
	ζ_{13}	This DBS combines an AI-integrated knowledge base with the knowledge to offer comprehensive financial services interchangeably	4.78	1.01	0.91
	ζ_{14}	This DBS has an AI-integrated service delivery system for various financial products and services	4.82	1.04	0.90
Banking corporate reputation (ζ_2)	Reference:	Heinberg *et al.* (2018), Oghazi *et al.* (2021)			
	ζ_{21}	This DBS is well respected	5.12	1.03	0.84
	ζ_{22}	Some characteristics of this DBS come to mind very quickly	4.85	1.04	0.90
	ζ_{23}	I can quickly recall the symbol or logo of this DBS	4.56	1.23	0.77
	ζ_{24}	Overall, this DBS has a reputation for providing friendly service	4.81	1.04	0.83
Digitalised banking service (DBS) assessment (ζ_3)	Reference:	Payne *et al.* (2021)			
	ζ_{31}	I am comfortable using an AI-integrated automated voice menu (and/or visual screen menu) with this DBS	4.36	1.17	0.85
	ζ_{32}	I am comfortable conversing with an AI-integrated automated service concerning my personal and transaction information with this DBS	4.35	1.18	0.90
	ζ_{33}	I am comfortable receiving personalised investment advice from the AI-integrated automated service offered by this DBS	4.31	1.16	0.88
	ζ_{34}	Overall, I am comfortable using an AI-integrated service with this DBS	4.43	1.15	0.89
Intention to recommend DBS (ζ_4)	Reference:	Hsieh and Lee (2021)			
	ζ_{41}	I would recommend this DBS for: Essential access to a user's account	4.51	1.22	0.85
	ζ_{42}	Greater control for managing personal finances	4.51	1.16	0.89
	ζ_{43}	Protection against digital fraud and cybersecurity attacks	4.52	1.13	0.86
	ζ_{44}	Fast banking	4.84	1.12	0.82
	ζ_{45}	Banking information that customers need	4.55	1.14	0.88

Note(s): (1) AI, artificial intelligence; DBS, digitalised banking services; IT, information technology; (2) All factor loadings are significant at 0.01; (3) SD, standard deviation; (4) FL, factor loadings

Source(s): Authors' own creation

factor loadings were significant ($p < 0.001$), with minimum and maximum loadings of 0.77 and 0.91, respectively.

Table 4 presents the correlations among latent variables along with the values for Cronbach's alpha, composite reliability, rho_A (Dijkstra and Henseler's composite reliability), average variance extracted (AVE), the square root of AVE, and the heterotrait-monotrait (HTMT) ratio of correlations (Fornell, 1992; Hair *et al.*, 2020; Henseler *et al.*, 2016).

Table 4. Construction reliability, validity, and HTMT ratio

	ζ_1	ζ_2	ζ_3	ζ_4
ζ_1	(0.90)			
ζ_2	0.72	(0.84)		
ζ_3	0.60	0.66	(0.88)	
ζ_4	0.58	0.77	0.75	(0.86)
Cronbach's alpha	0.92	0.86	0.90	0.91
Composite reliability (rho_a)	0.92	0.86	0.91	0.91
Composite reliability (rho_c)	0.94	0.90	0.93	0.93
Average variance extracted (AVE)	0.80	0.70	0.77	0.74

Note(s): HTMT, heterotrait-monotrait; Diagonals in parentheses represent the square root of the AVE
Source(s): Authors' own creation

The hypothesised model demonstrated acceptable internal consistency, as indicated by Cronbach's alpha, composite reliability, and rho_A values meeting or exceeding the threshold of 0.7. Internal consistency was confirmed using the composite reliability index (>0.70) and Cronbach's alpha (>0.70). The AVE exceeded the threshold (>0.50), indicating the constructs' reliability and convergent validity. The model's discriminant validity was assessed by comparing the AVE and correlation coefficients. The hypothesised correlations in the model were also validated, with all latent variables showing significantly positive relationships ($p < 0.05$).

4.6 Common method bias test

This study assessed the model for common method bias (CMB) through multiple tests (Hamzah *et al.*, 2020). First, Harman's single-factor approach was adopted to ensure that no single factor explained more than 50% of the variance in the measurement variables (Podsakoff *et al.*, 2003). Next, a full collinearity test was conducted to confirm that all variance inflation factor (VIF) values in the inner model were below 3.3, indicating no significant CMB (Kock, 2017). The results showed VIF values ranging from a minimum of 1.65 to a maximum of 1.96, all below the conservative threshold of 3.3. These findings demonstrated that CMB was not a significant concern in this study.

5. Empirical results

5.1 Structural model evaluation using PLS-SEM

Figure 2 depicts the hypothesised model's PLS-SEM results, including the standardised coefficient. All hypotheses were supported except for H3. AI-integrated banking services and corporate reputation significantly positively affected customers' DBS assessment ($\beta = 0.297$ and 0.393, respectively) at the 0.001 level. Customers' DBS assessment positively affected intention to recommend DBS ($\beta = 0.423$). Interestingly, while corporate reputation positively affected intention to recommend DBS ($\beta = 0.419$), AI-integrated banking service did not significantly affect intention to recommend DBS with a p-value of 0.536.

By investigating the explanatory power (R-squared, R^2) of each endogenous variable, this study found that DBS assessment and behavioural intention to recommend DBS were 0.393 and 0.590, respectively, indicating that the degree of explanation for converged latent variables by the exogenous variables range weak to moderate. Finally, the PLSpredict technique was utilised to assess the relevance of the proposed paths as part of the causal prediction results (Shmueli *et al.*, 2019). The adopted approach assesses robust predictive abilities by comparing PLS-SEM and linear model (LM) outcomes, focusing on prediction errors (RMSE and MAE). That is, when PLS-SEM shows lower predictor errors than LM, predictive capacity is

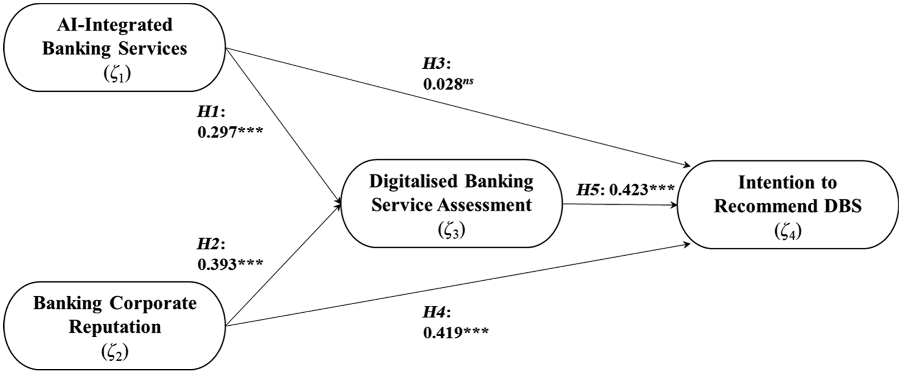

Figure 2. Results of structural equation. Notes: ***$p < 0.001$; ^{ns} $p > 0.05$. Source: Authors' own creation

considered high (Chanda *et al.*, 2025; García-Fernández *et al.*, 2018). In this study (Table 5), the model demonstrates medium predictive power, as four indicators of PLS-SEM outperformed two indicators of LM in both DBS assessment and intention to recommend.

5.2 Mediating effect of DBS assessment on AI-integrated banking services

Tables 6 and 7 summarise the direct and indirect effects and the mediation effects of DBS assessment, respectively. Furthermore, the contribution of the variables (f-squared, f^2) and the

Table 5. Results of PLS-predict

Indicators	PLS RMSE	PLS MAE	LM RMSE	LM MAE	PLS – LM RMSE	PLS – LM MAE	Q^2 predict
ζ_{31}	1.043	0.815	1.071	0.839	−0.028	−0.024	0.163
ζ_{32}	1.030	0.797	1.038	0.805	−0.008	−0.008	0.273
ζ_{33}	1.011	0.777	0.984	0.774	0.027	0.003	0.225
ζ_{34}	0.981	0.755	0.966	0.725	0.015	0.030	0.262
ζ_{41}	1.081	0.813	1.074	0.824	0.007	−0.011	0.303
ζ_{42}	0.955	0.684	0.981	0.708	−0.026	−0.024	0.279
ζ_{43}	1.018	0.774	1.019	0.788	−0.001	−0.014	0.210
ζ_{44}	0.841	0.667	0.836	0.666	0.005	0.001	0.346

Note(s): ζ_{31} through ζ_{34}: indicators of digitalised banking service (DBS) assessment; ζ_{41} through ζ_{44}: indicators of intention to recommend DBS
Source(s): Authors' own creation

Table 6. Summary of direct and indirect effects

Hypotheses		Direct	Indirect	Total	f^2
H5a AI-integrated banking services	→ DBS assessment	0.297		0.297	0.26^c
	→ Intention to recommend DBS	0.028	0.126	0.154	0.10^b
H5b Banking corporate reputation	→ DBS assessment	0.393		0.393	0.01^a
	→ Intention to recommend DBS	0.419	0.166	0.586	0.15^b
H5 DBS assessment	→ Intention to recommend DBS	0.423		0.423	0.22^c

Note(s): (1) DBS, digitalised banking services; (2) ^{a} small effect, ^{b} medium effect, ^{c} large effect
Source(s): Authors' own creation

Table 7. Significance testing of indirect effects with bootstrapping

Statistics	AI-integrated banking services	Banking corporate reputation
Indirect effect	0.126	0.166
Standard error	0.023	0.027
z-statistics	5.478	6.148
p-value	0.00	0.00
NCI	(0.081, 0.171)	(0.113, 0.219)
PCI	(0.082, 0.171)	(0.116, 0.225)
BCCI	(0.084, 0.175)	(0.117, 0.226)

Note(s): (1) 5,000 interactions of bootstrapping; (2) confidence level 95%; (3) NCI = normal confidence interval, PCI = percentile confidence interval, BCCI = bias-corrected confidence interval

Source(s): Authors' own creation

influence of exogenous variables were investigated to determine the effect size as small, medium, or large (Hair *et al.*, 2017). The results reveal key insights into the direct, indirect, and total effects of (1) AI-integrated banking services, (2) banking corporate reputation, and (3) DBS assessment on the intention to recommend digitalised banking services (DBS).

First, AI integration directly affects assessments (0.297), implying that AI integration is critical in determining customers' assessments of DBS. However, its direct influence on the intention to recommend DBS is minimal (0.028). Instead, an indirect notable impact of AI integration (0.126) emerges through DBS assessment, indicating that customers' DBS assessment mediates the relationship. This assessment results in a moderate total effect (0.154, medium effect, $f^2 = 0.10$).

Second, banking corporate reputation directly impacts DBS assessment (0.393), indicating its role in affecting customer assessment and behavioural intention of recommending DBS. Its direct influence on the intention to recommend DBS is also strong (0.419), with an additional indirect effect (0.166) mediated through DBS assessment. This collective relationship leads to a total effect (0.586, medium effect, $f^2 = 0.15$), implying its dual impacts (direct and mediated) on fostering customers' recommendation behaviour through corporate reputation.

Third, DBS assessment strongly and directly influences customer intention to recommend DBS (0.423, large effect, $f^2 = 0.22$), indicating its solid role as a key determinant of customer recommendation intention.

Lastly, as illustrated in Table 7, the indirect effects of AI-integrated banking services and corporate banking reputation are further examined with the significance testing using bootstrapping. For AI-integrated banking services, the indirect effect is 0.126, with a standard error of 0.023 at a highly significant level ($p < 0.001$). Similarly, for banking corporate reputation, the indirect effect is 0.166 with a standard error of 0.027 and a high statistical significance ($p < 0.001$). Within the confidence intervals (NCI, PCI, and BCCI), no paths included zero, thus confirming the significance of these indirect effects. The results provide robust statistical support for the significant indirect effects of AI-integrated banking services and banking corporate reputation.

5.3 Multi-group analysis of customers' financial knowledge and attitudes towards promotions

To advance the initial structural model (H1–H5), a multi-group analysis (MGA) was conducted in response to recent calls for a socioeconomic perspective in DBS delivery systems. Specifically, this study incorporates theory-driven approaches to investigate participants' financial knowledge levels (H6a–H6d) and gain motivation through promotion (H7a–H7d). This additional analysis aims to (1) validate the empirical role of additional factors influencing the overall DBS evaluation and (2) determine how DBS service providers should leverage the findings for marketing and service operation strategies.

This study incorporates participants' financial knowledge based on financial literacy indicators adopted from the research (Okamoto and Komamura, 2021) and attitudes towards promotion based on previous findings (Jiang *et al.*, 2021). Appendix summarises the indicators for categorising participants into the different groups, of which the lowest and highest groups were used for an in-depth understanding of group behaviour. Tables 8 and 9 report the path-specific MGA results. These results compare the low and high groups based on (1) financial knowledge and (2) attitudes toward promotions, as shown in Figure 3.

First, in the case of financial knowledge (Table 8), except for H6c (banking corporate reputation → DBS assessment), the hypothesised relationships remain consistent across low and high financial knowledge groups. AI-integrated banking services similarly impact both groups' DBS assessment (H6a) and recommendation intentions (H6b). Lastly, banking corporate reputation plays a stronger role in DBS assessment for the low financial knowledge group (H6c), while its influence on recommendation intentions (H6d) is consistent across both groups.

Second, in the case of attitudes towards promotion (Table 9), except for H7a (AI-integrated banking services → DBS assessment), the hypothesised relationships remain stable across low and high attitudes towards promotion groups. AI integration has a more substantial impact on DBS assessment for participants with high attitudes toward promotions (H7a), but its effect on recommendation intentions (H7b) remains stable across groups. Banking corporate reputation

Table 8. Multi-group comparison test with financial knowledge

Hypotheses		Low	High	|Low – High|	*t*-value	*p*-value
AI-integrated banking services						
H6a	→ DBS assessment	0.206	0.270	0.065	0.490	0.624^{ns}
H6b	→ Intention to recommend DBS	0.108	0.082	0.015	0.126	0.900^{ns}
Banking corporate reputation						
H6c	→ DBS assessment	0.592	0.340	0.257	1.977	0.048**
H6d	→ Intention to recommend DBS	0.338	0.394	0.050	0.365	0.715^{ns}

Note(s): ***p* < 0.05; ^{ns} *p* > 0.05
Source(s): Authors' own creation

Table 9. Multi-group comparison test with attitudes towards promotion

Hypotheses		Low	High	|Low – High|	*t*-value	*p*-value
AI-integrated banking services						
H7a	→ DBS assessment	0.103	0.356	0.259	1.986	0.047**
H7b	→ Intention to recommend DBS	0.047	−0.024	0.071	0.587	0.557^{ns}
Banking corporate reputation						
H7c	→ DBS assessment	0.526	0.286	0.245	1.805	0.071^{ns}
H7d	→ Intention to recommend DBS	0.375	0.433	0.069	0.525	0.599^{ns}

Note(s): ***p* < 0.05; ^{ns} *p* > 0.05
Source(s): Authors' own creation

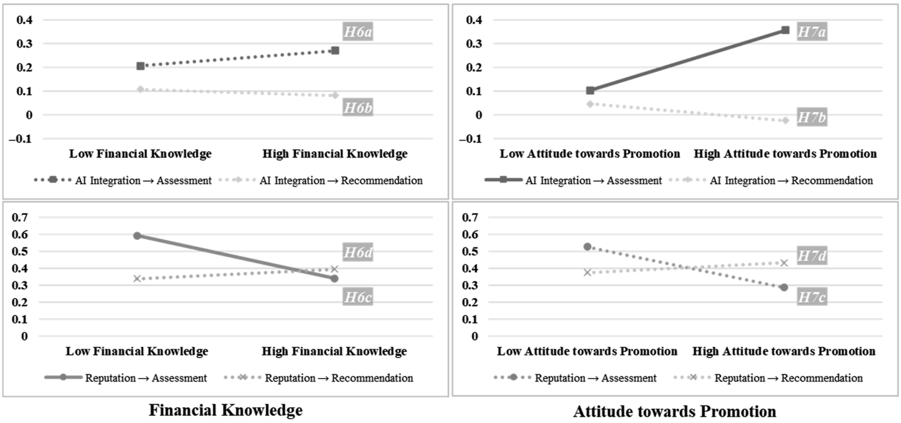

Figure 3. Moderation effect of financial knowledge (left) and attitudes towards promotion (right). Source: Authors' own creation

slightly favours DBS assessment in the low promotion attitude group (H7c), though its impact on recommendation intentions (H7d) is consistent across both groups.

6. Discussion

The results are discussed in two sections: (1) the statistically significant roles of banking service characteristics (AI-integrated banking services and corporate reputation) on customers' DBS assessment, and how this assessment mediates the relationship with recommendation behaviour; and (2) the role of customer characteristics (attitudes towards promotion and financial knowledge) in gaining users' confidence in their banking experience.

6.1 DBS: AI integration and corporate reputation

The findings present two key insights: (1) both AI integration and reputation play crucial roles in customer's perception of DBS, and (2) DBS assessment is a significant mediator for AI integration and facilitator to customers' transitions to DBS on recommendation behaviour, providing valuable insights for DBS management.

First, technological integration and corporate reputation offer valuable insights into user behaviour from an integrative operational perspective (H1 and H2). These findings strengthen the importance of technological and reputational approaches to the recent academic focus on AI-embedded service management. Specifically, they provide novel insights into the need for collaborative efforts in AI integration and reputation management. For example, Previous studies found that corporate reputation significantly influences AI-based digital banking acceptance (Candiwan and Annikmah, 2024) and that neobanks should align with parent brand reputation to enhance customer experience (Mogaji and Nguyen, 2024). The integrated approach proposed in this study highlights the potential for synergy between technological innovation and reputation management in enhancing the overall customer experience with DBS.

Second, the direct effects of AI integration and corporate reputation on users' recommendation behaviour differ (H3 and H4). The insignificant direct effect of AI-integrated banking services may stem from users' evolving behaviours with smart devices and AI applications (Wang *et al.*, 2022). Users often perceive AI features as distinct from service quality, limiting their direct impact on recommendations (Barone *et al.*, 2024). Most importantly, AI-integrated services and corporate reputation indirectly influence recommendation intentions through DBS assessment (H5a and H5b), aligning with prior conceptual work (Andreassen and Lindestad, 1998; Payne *et al.*, 2021). The findings confirm that positive experiences and satisfaction remain crucial for customer retention, as AI alone cannot secure loyalty without favourable DBS assessments (Mogaji and Nguyen, 2024). AI integration must lead to higher DBS assessments to foster recommendations, as customers may perceive AI as separate from the overall service experience (Barone *et al.*, 2024) or as a long-term solution (Nishant *et al.*, 2020). These findings underscore the importance of evaluation-based constructs in understanding customer behaviour in digital banking.

That is, a gap between AI implementation and customers' perception of its impact on service experience can affect recommendation behaviour, underscoring the vital role of DBS assessment (H5). This finding highlights the growing importance of digital services in banking and the need for banks to build customer confidence for successful service adoption and recommendations. User confidence in digital services is crucial for digital transformation, including AI-driven services (Sheth *et al.*, 2022), privacy measures (Payne *et al.*, 2021), and ethical transparency (Casheekar *et al.*, 2024). Integrating IT infrastructure and AI in banking enhances trust beyond AI-powered services like financial advice or chatbots. Studies show that user satisfaction fosters recommendations, while technologies like facial recognition boost trust in digital banking (Shahzad *et al.*, 2024; Zhu *et al.*, 2022). Clear explanations of AI's role in decisions, such as credit scoring, strengthen trust and increase recommendations (Barone *et al.*, 2024; Hamakhan and Taha, 2020; Urbani *et al.*, 2024).

This study underscores the need for collaboration between AI-integrated banking services and corporate reputation while ensuring high DBS assessments for successful adoption. Banks must balance technology integration, reputation, and customer assessment in the digital landscape to stay competitive.

6.2 Assessment of DBS: attitudes towards promotion and financial knowledge

This study examined the impact of AI integration and corporate reputation on DBS assessment, considering factors such as customer attitudes towards promotion and financial knowledge. The research addresses how these banking service characteristics influence customer decision-making in the context of increasing social interaction and the societal need for financial inclusion. Two key relationships emerge: (1) AI integration and promotional attitude, and (2) corporate reputation and financial knowledge.

The first relationship suggests that customers receptive to digital promotions view AI integration more favourably in the banking experience (H7a), offering insights into engagement strategies via digital channels. While social media marketing's effectiveness remains debated (Bapat, 2021), our findings suggest that when promotions create positive experiences, open-minded customers assess AI integration more positively in DBS. In contrast, there was no significant evidence as to whether the low- or high-financial knowledge groups perceived the impact of AI integration differently (H6a). Customers with different levels of financial knowledge do not differ in assessing the relationship between AI integration and the banking experience; that is, whether customers have low or high financial knowledge, their perception of AI integration will not have varying impacts on the banking experience. This experience indicates the need for a clear distinction between digital and financial knowledge when determining the digital financial knowledge of users (Bunnell *et al.*, 2021). According to GFT, these results confirm that gain-oriented goals positively influence customers' assessments of AI-integrated banking services, particularly among those receptive to digital promotions. Moreover, the lack of significant differences between low- and high-financial knowledge customer groups suggests that the motivation to maximise benefits may be a consistent factor determining customers' assessments of DBS.

The second key relationship identified in this study reveals a significant connection between corporate reputation and financial knowledge in the context of DBS assessment. Specifically, customers with lower financial knowledge demonstrated a higher impact of corporate reputation on their overall DBS assessment (H6c). This finding suggests that individuals with less financial expertise tend to rely more heavily on a bank's reputation when evaluating digital banking services. This result has key implications, reinforcing corporate reputation benefits (Money *et al.*, 2017) and digital banking decision-making (Zhao *et al.*, 2023). IT firms entering digital banking may struggle with trust, especially among less financially savvy users. Collaborations with traditional banks can help by combining IT expertise with established reputations, fostering AI integration success (Hornuf *et al.*, 2020). Conversely, no evidence supports differences in corporate reputation's impact on behaviour across promotional attitude levels (H7c). This suggests that promotions primarily enhance monetary benefits rather than creating significant experiences (Shah *et al.*, 2024). Additionally, recommendation behaviour remained unchanged across financial knowledge and promotional attitude groups (H6b, H6d, H7b, H7d), suggesting no meaningful differences. From a GFT perspective, customers with lower financial knowledge who seek to maximise benefits are likely to use corporate reputation as a reference when assessing DBS. That is, customers may have a primary interest in securing a beneficial banking experience, particularly when their own expertise (i.e. financial knowledge) is limited.

Overall, the findings highlight the relationship between users' adoption of DBS and customer characteristics, such as attitudes towards promotions and financial knowledge. These insights are valuable for both traditional and internet-only banks in the evolving digital finance landscape.

7. Conclusion and future studies

This study's results extend the theoretical knowledge by clarifying the impacts of AI-integrated banking services and corporate reputation on customers' assessment of and intention to recommend DBS and the differences among customers' characteristics (i.e. financial knowledge and attitudes towards promotions). Specifically, two research topics are addressed: (1) The potential synergistic outcome of AI integration and corporate reputation in driving the user's acceptance of the digitally transformed banking services and (2) the significance of customer characteristics such as promotional attitude and financial knowledge in designing digital banking experiences that can ultimately foster recommendation behaviour.

This study clarifies the relationship based on the GFT perspective, which can be used to optimise DBS design and delivery strategies. Particularly, this study offers theoretical insight into GFT. By integrating AI-driven services and leveraging corporate reputation, banks can establish clear, targeted goals for customers through digital promotions and other immediate rewards, while also creating opportunities to engage users with diverse levels of financial knowledge. Moreover, understanding how customer traits activate different goal frames as outlined by GFT (Lindenberg and Steg, 2007), can help both traditional and internet-only banks design DBS and promotions to better motivate and engage their customers. This study also offers practical insights into service design strategies for diverse customer groups. While prior DBS research emphasises financial knowledge and literacy, the findings highlight the importance of incorporating a responsible finance perspective to address the role of core financial knowledge in digital financial literacy. Additionally, with the growing use of social promotions and active marketing in DBS, the study underscores the need to reassess customers' attitudes toward promotions.

The findings carry significant implications for stakeholders. From a policy perspective, they call for more straightforward guidelines on AI-based financial services, particularly for less financially literate customers. They also advocate for national strategies to enhance digital financial education for underserved groups. The results highlight the importance of aligning technological innovations with long-term reputation management for financial institutions to reach diverse customer segments effectively. Designing inclusive service interfaces and utilising trust-building strategies can support engagement, especially among users with limited financial knowledge. From a societal perspective, the study ignites a discussion for broader educational initiatives that raise awareness of the cognitive effects of digital promotions. Improving consumers' understanding of financial judgment, digital incentives, and AI-related risks could contribute to more informed and balanced digital banking behaviour.

This study has several limitations related to its factors, model coverage, and empirical examination. First, customers' perceptions of AI-integrated banking services can be adopted into an experimental study setting to more accurately incorporate customers' level of understanding from mere automation to generative AI services. Second, the study model attempted to cover various IT, DBS, and customer characteristics but failed to provide a comprehensive approach for systematically identifying the key characteristics. Therefore, in future, the hypothesised relationships and model can be better supported by revising the key measurement variables, such as the technological, societal, and operational factors. Third, the study was conducted in South Korea, where traditional banks undergo disruptive changes, and internet-only banks are subject to strict government banking regulations. Therefore, this setting may be considered relatively conservative compared to other regional settings that allow more internet-only banks to engage in the financial industry. Thus, to improve the generalisability of the findings, future research should examine regions with different levels of government participation in banking and fintech regulations.

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Appendix
The financial knowledge construct included participants who answered three to four questions incorrectly (low: $n = 153$ [46.79%]) and those who answered all questions correctly (high: $n = 190$ [52.21%]). The attitudes towards promotions construct included participants who had registered for a banking account to receive a promotional coupon or shown interest in choosing a DBS to receive a better promotion.

The groups were formed based on those who indicated no engagement (low: $n = 190$ [47.26%]) and high engagement (high: $n = 212$ [52.74%]) with the two constructs and those who answered "yes" to all indicators. Both variables were measured using a dichotomous "yes or no" scale rather than a Likert scale, to provide clear and objective categorisation of respondents' financial knowledge and attitudes towards promotions.

Table A1. Constructs and indicators for low and high customer groups

Construct	Indicator
Financial knowledge	1. If you invested USD 100 today and the interest rate was 2% per year, your account balance after 5 years would be USD 102
	2. After 1 year, you could buy more than today if you invested USD 100 in your account today at an interest rate of 1% per year when inflation is 2% per year
	3. Buying shares in a single company usually provides safer returns than buying shares in a managed share fund
	4. A 15-year mortgage typically requires higher monthly payments than a 30-year mortgage, but the total interest paid over the life of the loan will be less
Attitudes towards promotions	1. I have heard of promotions (e.g. a free cup of coffee) associated with a specific mobile financial service application
	2. I previously received a free promotion coupon when I opened an account
	3. If two mobile financial service applications offered the same interest rates and conditions for financial transactions, I would choose the one that offers a free coupon
	4. Overall, I think that mobile financial service application products are often similar, and I tend to make decisions based on the availability of promotions

Source(s): Authors' own creation

Table A2. Descriptive statistics for customer groups by constructs

Construct	Group	*N*	%	Criteria
Financial knowledge	Low	153	46.79%	3–4 incorrect answers
	High	190	52.21%	All correct answers
Attitudes towards promotions	Low	190	47.26%	No engagement (answered “no” to all indicators)
	High	212	52.74%	High engagement (answered “yes” to all indicators)

Source(s): Authors’ own creation

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