

From Artificial Intelligence to Customer Advocacy: Evidence from the Banking Industry

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Abstract

Research Originality: This study contributes to the literature by integrating technological, relational, and behavioral perspectives and mechanisms to explain how AI-enabled banking services may translate into customer advocacy through Brand Trust, Customer Engagement, and Customer Satisfaction.

Research Objectives: This study examines the direct and indirect effects of Artificial Intelligence on Brand Trust, Customer Engagement, Customer Satisfaction, and positive word-of-mouth (PWOM), with particular attention to the mediating roles of these customer relationship constructs.

Research Method: We surveyed 484 Indonesian banking customers using AI-enabled services and analyzed the data through Partial Least Squares Structural Equation Modeling (PLS-SEM).

Empirical Results: The findings indicate that AI capability positively influences Brand Trust, Customer Engagement, and PWOM, with Brand Trust emerging as the most prominent mechanism associated with customer advocacy. Customer Engagement also positively influences Customer Satisfaction; however, Customer Satisfaction does not significantly influence PWOM.

Implications: The findings suggest that successful AI implementation in banking should extend beyond technological performance to encompass relationship building. Strengthening Brand Trust should therefore be a strategic priority, as trust appears to provide a stronger foundation for customer advocacy than Customer Satisfaction alone.

Keywords:

financial technology, service innovation, consumer behavior, information systems, PLS-SEM

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INTRODUCTION

Artificial Intelligence (AI) has evolved from a primarily operational technology into a key capability for transforming customer-facing services in the banking industry (Dwivedi, 2021). Banks increasingly use AI through intelligent chatbots, virtual assistants, automated service interactions, predictive analytics, and personalized digital services to improve responsiveness, efficiency, information provision, and customer experience (Chen & Prentice, 2025). Research on AI in commercial banking indicates that AI can improve operational efficiency, security, customer targeting, and service delivery, although its successful implementation also depends on customer acceptance and behavioral responses (Ho & Chow, 2024; Mogaji & Nguyen, 2022; Sheth et al., 2022). From a customer perspective, AI-enabled services are evaluated by convenience, personalization, interaction quality, and service performance, while trust remains an important condition for translating technological capabilities into favorable customer experiences (Ameen et al., 2021; Chen & Prentice, 2025). Similarly, Alagarsamy & Mehroliya (2023) demonstrate that trust is an important determinant of customers' responses to banking chatbots. These findings indicate that AI should be understood not simply as a technological tool, but as a service capability that can influence the quality and development of customer bank relationships.

In banking, AI-enabled chatbots and intelligent service systems have increasingly become important customer touchpoints. Previous studies indicate that chatbot characteristics, service quality, information quality, and system performance can shape customers' evaluations and behavioral intentions (Dwivedi, 2021; Mulyono & Sfenrianto, 2022; Trivedi, 2019). Nguyen et al. (2021) further demonstrate that trust is a particularly important determinant of customers' continued use of banking chatbot services. At the relational level, chatbot-enabled interactions can also foster customer engagement when customers perceive the technology as interactive, compatible, and useful (Hari & Iyer, 2021). More recent research continues to demonstrate that AI-enabled banking services can enhance customer satisfaction and other favorable customer outcomes (Alnaser et al., 2023; Hang et al., 2026). Accordingly, the strategic value of AI should be assessed not only through technological adoption or operational efficiency but also by its potential to support trust, engagement, satisfaction, and favorable behavioral responses.

Despite this growing body of literature, an important question remains concerning what occurs after customers experience AI-enabled banking services. Existing studies have predominantly examined technology acceptance, continuance intention, customer satisfaction, and loyalty (Alnaser et al., 2023; Königstorfer & Thalmann, 2020; Nguyen et al., 2021). Although these outcomes matter, they do not fully explain whether AI-enabled service experiences translate into customer advocacy, particularly positive word-of-mouth (PWOM). Unlike satisfaction or continued usage, PWOM represents customers' willingness to recommend a bank and communicate positively about its services. Research on customer advocacy conceptualizes positive word-of-mouth as a distinctive behavioral outcome involving customers' active and voluntary support of a brand (Sweeney et al.,

2020). Recent studies also indicate that AI-enabled service experiences can influence customers' willingness to recommend or communicate positively about AI-supported services (Pang et al., 2026; Yun & Park, 2022). However, the mechanisms through which AI capability translates into customer advocacy remain insufficiently integrated and empirically examined in the banking literature.

This issue is particularly important in the Indonesian banking industry, where digital banking and AI-enabled customer services are becoming increasingly important components of customer interaction. Evidence from Indonesia indicates that banking chatbot quality, including system- and service-related dimensions, can influence customer satisfaction and intention to use chatbot services (Mulyono & Sfenrianto, 2022). Other studies on Indonesian banking customers have highlighted the importance of trust in shaping customer responses to chatbot-based services (Aji et al., 2023). These findings demonstrate the relevance of AI-enabled service quality and trust in the Indonesian context; however, they provide limited insight into how such technological and relational factors ultimately translate into customer advocacy (Riedel et al., 2022). Consequently, a more integrated framework is needed to explain how customers progress from experiencing AI-enabled services to developing trust, engaging with the bank, evaluating their experience, and ultimately recommending the bank to others (Sweeney et al., 2020).

An important academic debate therefore concerns whether AI should be conceptualized primarily as a technological artifact or as a broader service capability embedded within customer relationships. Much of the existing literature emphasizes technology adoption, perceived usefulness, ease of use, behavioral intentions, and continuance of use. Although these perspectives explain why customers adopt and continue using emerging technologies, they provide less insight into relational and behavioral consequences. Trivedi (2019), for example, demonstrates the importance of customer experience in shaping evaluations of banking chatbots, while Hari & Iyer (2021) show that chatbot interactions can foster customer brand engagement. Alagarsamy & Mehrolia (2023) further emphasize the role of trust in shaping customer responses to banking chatbot experiences. Taken together, these studies suggest that AI should be examined beyond technology adoption and conceptualized as a multidimensional service capability whose perceived quality can shape both technological evaluations and relational responses.

This study addresses this conceptual issue by integrating the Information Systems Success Model (ISSM) with a relationship-oriented perspective. ISSM provides a suitable foundation for conceptualizing AI-enabled banking services through Information Quality, System Quality, and Service Quality because customers experience AI-enabled services through the quality of information provided, system performance and usability, and service support during AI-mediated interactions (Mulyono & Sfenrianto, 2022; Trivedi, 2019). Recent research further supports the relevance of ISSM-related quality dimensions in explaining customer responses to AI-enabled services (Hang et al., 2026). At the relational level, Brand Trust is an important mechanism because customers

must develop confidence in the bank and its AI-enabled services before forming deeper relational responses. This perspective is consistent with evidence linking AI-enabled customer experiences and chatbot characteristics with customer trust (Alagarsamy & Mehroliya, 2023; Ameen et al., 2021; Chi & Hoang Vu, 2023). Customer Engagement is subsequently conceptualized as an important relational response because interactive AI services can encourage customers to participate more actively in their relationships with the bank (Hari & Iyer, 2021; Kumar & Pansari, 2016), while Customer Satisfaction represents customers' overall evaluation of their service experiences (Alnaser et al., 2023). PWOM is positioned as a behavioral manifestation of customer advocacy (Sweeney et al., 2020).

Several specific research gaps can therefore be identified. First, an outcome gap remains, as previous research on AI in banking has focused predominantly on technology adoption, continuance intention, customer satisfaction, and loyalty, while Positive Word-of-Mouth (PWOM) as an indicator of customer advocacy has received comparatively limited attention (Alnaser et al., 2023; Königstorfer & Thalmann, 2020). Although Yun & Park (2022) demonstrate that chatbot service characteristics can influence satisfaction and positive word-of-mouth, and Pang et al. (2026) identify relationships between information interactivity, trust, involvement, and PWOM in AI-powered chatbots, these studies do not provide an integrated explanation of how AI-enabled service capabilities may translate into customer advocacy in the banking context. Second, a mechanism gap concerns the limited integration of Brand Trust, Customer Engagement, Customer Satisfaction, and PWOM; these constructs have often been examined separately or in more limited combinations, leaving their interrelationships within an integrated AI-enabled banking framework insufficiently understood. Third, a satisfaction-to-advocacy gap remains. Although chatbot service characteristics have been associated with both customer satisfaction and PWOM (Yun & Park, 2022), it remains unclear whether customer satisfaction alone is sufficient to translate AI-enabled service experiences into customer advocacy in banking. Fourth, a trust-to-advocacy gap emerges. While trust has been established as an important factor in chatbot acceptance, continuance, and customer responses (Alagarsamy & Mehroliya, 2023; Chi & Hoang Vu, 2023), its role as a direct pathway to PWOM within an integrated banking model remains insufficiently examined. Fifth, a conceptualization gap arises from the tendency to examine AI primarily through technology-adoption variables or individual technological characteristics rather than as a broader service capability incorporating Information Quality, System Quality, and Service Quality (Mulyono & Sfenrianto, 2022; Trivedi, 2019). Finally, a contextual gap remains because empirical evidence integrating these technological, relational, and behavioral mechanisms among Indonesian banking customers is still limited (Luo et al., 2019; Aji et al., 2023).

This study's novelty lies in developing an integrated AI-to-customer-advocacy framework that distinguishes the roles of technological capability, Brand Trust, Customer Engagement, and Customer Satisfaction rather than treating them as isolated outcomes.

First, the study extends the Information Systems Success Model (ISSM) from technology-related outcomes to relational and behavioral outcomes by conceptualizing AI capability through Information Quality, System Quality, and Service Quality (Jeyaraj, 2020; Wang et al., 2026). Second, it integrates technological quality with relationship-oriented mechanisms by examining Brand Trust as a central relational construct linking AI capability with Customer Engagement, Customer Satisfaction, and Positive Word-of-Mouth (PWOM) (Khan & Fatma, 2023; Tulcanaza-Prieto et al., 2023). Third, the study provides a more differentiated explanation of customer advocacy by empirically examining the respective roles of Brand Trust, Customer Engagement, and Customer Satisfaction in predicting PWOM. This distinction matters because previous research shows that chatbot characteristics can influence both satisfaction and PWOM (Yun & Park, 2022), while trust has emerged as a central factor in AI-enabled banking interactions (Alagarsamy & Mehroliya, 2023; Ameen et al., 2021). Fourth, the study contributes empirical evidence from Indonesian banking customers with direct experience using AI-enabled services, complementing previous Indonesian studies that have focused more narrowly on chatbot quality, satisfaction, trust, or usage intention (Mulyono & Sfenrianto, 2022; Aji et al., 2023)

Accordingly, this study examines the direct and indirect effects of AI capability on Positive Word-of-Mouth through Brand Trust, Customer Engagement, and Customer Satisfaction among Indonesian banking customers. Specifically, it tests whether AI capability strengthens Brand Trust, Customer Engagement, and PWOM; whether Brand Trust enhances Customer Engagement and Customer Satisfaction; and whether Brand Trust, Customer Engagement, and Customer Satisfaction are associated with PWOM. The study also examines whether Customer Satisfaction contributes to PWOM independently or whether Brand Trust and Customer Engagement provide additional relational pathways to customer advocacy. By examining these relationships simultaneously, the study moves beyond a primary focus on AI adoption and continuance to investigate how AI-enabled banking capabilities relate to trust, engagement, satisfaction, and ultimately customer advocacy.

METHODS

The study used a cross-sectional design, a quantitative approach, and a survey method to evaluate Artificial Intelligence (AI) Capability, Brand Trust, Customer Engagement, Customer Satisfaction, and Positive Word-of-Mouth (PWOM) among Indonesian bank customers. The PLS-SEM method suggested by Hair et al. (2022) is appropriate for structural equation modeling with highly multivariate, non-normal data in predictive-oriented research where the relationships are not well understood, involving multiple latent variables and complex structural equations to estimate the specified relationship. Researchers used the data analysis software SmartPLS. In this study, Indonesian bank customers using AI services, including intelligent chatbots, virtual assistants, automated customer service, and AI-supported mobile banking apps, formed the target population.

Purposive sampling, a non-probabilistic approach, was used to recruit respondents because participation required them to meet specific criteria. At a minimum, respondents were 18 years of age or older, had a bank account, and had at least interacted with one AI-enabled banking service. To ensure respondents had sufficient experience to weigh in on whether they trusted, engaged with, Were Satisfied With, and Were Willing to recommend the bank because of AI-assisted banking services. Data were collected through a self-administered online survey questionnaire using Google Forms. The questionnaire was time-consuming and divided into three identifiable sections: instructions, measurement items, and demographic queries. Initially, 512 screens were viewed, and after testing eligibility, validity, and response consistency, 484 responses were sufficient for the final analysis.

Table 1. Constructs and items

Construct	Items	Sources
Artificial Intelligence (AI)	Information Quality	
	INFQ1: Bank X's chatbot delivers the information I require	
	INFQ2: Bank X's chatbot answers my queries appropriately	
	INFQ3: Bank X's chatbot supplies adequate necessary information	(Trivedi, 2019)
	INFQ4: I am satisfied with the precision of the information offered	
	INFQ5: The provided information effectively addresses my questions	
	System Quality	
	SISQ1: I can quickly learn how to use Bank X's chatbot	
	SISQ2: I think Bank X's chatbot is user-friendly	(Trivedi, 2019)
	SISQ3: Using Bank X's chatbot doesn't require much mental effort	
	SISQ4: Bank X's chatbot performs consistently and dependably	
	Service quality	
	SERQ1: I am pleased with the assistance provided by customer support	
	SERQ2: I am satisfied with the support received after the service	(Trivedi, 2019)
	SERQ3: Bank X's chatbot service is capable of understanding my concerns	
	SERQ4: Bank X's chatbot service delivers prompt responses	
Customer engagement	CE1:I am committed to Bank X and its services	
	CE2. I am enthusiastic about Bank X	
	CE3. I feel very positive about Bank X	(Hari & Iyer, 2021)
	CE4. I feel very active in using Bank X's services	
	CE5. I wholeheartedly support Bank X	
	CE6. I find it difficult to disengage when interacting with Bank X	

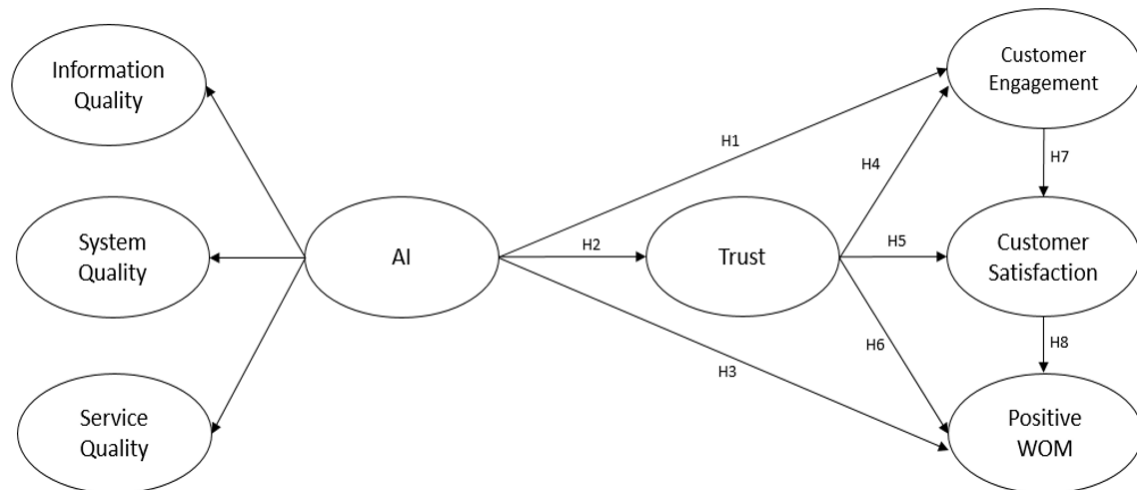
Construct	Items	Sources
Brand Trust	BT1: I trust Bank X	(Xue et al., 2020)
	BT2: I rely on Bank X	
	BT3: Bank X is safe	
	BT4: Bank X is an honest bank that meets my expectations	
Customer satisfaction	CS1. I feel content with the services provided by Bank X	(Manyanga et al., 2022)
	CS2. I am pleased with my overall experience with Bank X	
	CS3. In general, I am satisfied with my interactions with Bank X	
	CS4. I believe choosing Bank X was the right decision	
P-WOM	P-WOM1: I actively encourage friends and family to consider becoming customers of Bank X	(Manyanga et al., 2022)
	P-WOM2: I am likely to recommend Bank X when someone asks for advice	
	P-WOM3: If Bank X comes up in conversation online or offline I tend to speak positively about it	
	P-WOM4: I have shared recommendations about Bank X with my friends and family, both online and offline	

We evaluated sample adequacy using the 10-times rule, typically used in PLS-SEM research (Hair et al., 2022). The maximum number of structural paths leading to one endogenous construct was four, which imposed the lowest observation requirement of 40. With 484 valid responses, our final sample was substantively larger than this criterion, supporting its sufficiency for the planned PLS-SEM analysis. The exogenous construct was AI Capability, and the endogenous constructs were Brand Trust, Customer Engagement, Customer Satisfaction, and PWOM. AI Capability, as the higher-order construct, was built from Information Quality, System Quality, and Service Quality. We adapted existing scales and customized them for AI-enabled banking services. We adapted Information Quality, System Quality, and Service Quality from Trivedi (2019); Customer Engagement from Hari & Iyer (2021); Brand Trust from Xue et al. (2020); Customer Satisfaction from Manyanga et al. (2022); and PWOM from Manyanga et al. (2022). All items were measured on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The detailed measurement items and their sources are listed in Table 1.

We used SmartPLS 4 to test the measurement and structural models sequentially (Hair et al., 2019). As part of the evaluation, we assessed the measurement model using outer loadings, Cronbach's alpha, composite reliability, average variance extracted (AVE), and the heterotrait–monotrait ratio (HTMT), and we assessed VIF for multicollinearity. We tested the structural model using path coefficients, standard errors, t-values, p-values, and coefficients of determination (R^2), and confirmed its significance through bootstrapping. We examined indirect effects to establish the mediation of Brand Trust, Customer Engagement,

and Customer Satisfaction in the relationship between AI Capability and Positive Word-of-Mouth PWOM. Our analytical process involved a sequence of stages: data screening, measurement model testing, structural model testing, direct-effect testing, and indirect-effect analysis, as shown in Figure 1.

Figure 1. Conceptual Model of the Research



RESULTS AND DISCUSSION

The study initially received 512 responses, of which 484 valid responses were retained for the final analysis. Female respondents constituted 55% of the sample, while Generation Z respondents accounted for 70%. In terms of educational attainment, 58% of respondents held a bachelor's degree. Regarding employment status, 39% were full-time employees, and 35% were students. By bank ownership, 51% of respondents were customers of government-owned banks and 41% were customers of private banks. Overall, respondents indicate that the sample was predominantly composed of younger, relatively well-educated banking customers. Consider this demographic composition when interpreting the generalizability of the findings, particularly beyond younger customer segments. Table 2 presents the detailed respondent profile.

This section reports the results of the measurement and structural model assessments, followed by hypothesis testing and mediation analysis. As shown in Table 3, the measurement model satisfied the recommended criteria for indicator reliability, internal consistency reliability, convergent validity, and collinearity. The outer loadings exceeded the recommended threshold of 0.70, indicating satisfactory indicator reliability. Furthermore, the Cronbach's Alpha and Composite Reliability values met the recommended standards, confirming adequate internal consistency. The AVE values were also above 0.50, supporting convergent validity.

Table 2. Demographic Profile

Demographic Item	Response Option	Total	Percentage
Gender	Male	217	45%
	Female	267	55%
Generation	Gen Z (Born after 1994)	340	70%
	Gen Millennials (1977-1994)	74	15%
	Gen X (1965-1976)	67	14%
	Baby Boomers	3	1%
Education	High School	142	29%
	Bachelor's Degree	282	58%
	Master's Degree	47	10%
	Doctoral Degree	13	3%
Employment Status	Student	170	35%
	Full-Time Employee	188	39%
	Entrepreneur	36	7%
	Part-Time Employee	20	4%
	Unemployed	20	4%
	Others (Retired, Homemaker, etc.)	50	10%
Bank Type	Government-owned Bank	245	51%
	Private Bank	198	41%
	Islamic Bank	32	7%
	Foreign Bank	9	1%

Table 3. Measurement Model Results

Construct	ITEM	Outer Loading	Cronbach's	CR	AVE	VIF
AI (Artificial Intelligence)	INFQ1	0.753	0.941	0.949	0.609	2.144
	INFQ2	0.815				2.737
	INFQ3	0.768				2.226
	INFQ4	0.784				2.581
	INFQ5	0.802				2.925
	SERQ1	0.816				2.808
	SERQ2	0.824				3.003
	SERQ3	0.790				2.471
	SERQ4	0.733				1.940
	SISQ1	0.713				2.078
	SISQ2	0.766				2.366
	SISQ4	0.790				2.392

Construct	ITEM	Outer Loading	Cronbach's	CR	AVE	VIF
Brand Trust	BT1	0.820	0.847	0.898	0.687	1.909
	BT2	0.736				1.484
	BT3	0.884				2.568
	BT4	0.868				2.289
Customer engagement	CE1	0.780	0.912	0.932	0.696	1.982
	CE2	0.875				2.992
	CE3	0.860				2.687
	CE4	0.822				2.256
	CE5	0.866				2.782
	CE6	0.799				2.096
Customer satisfaction	CS1	0.898	0.906	0.934	0.781	3.247
	CS2	0.890				3.067
	CS3	0.880				2.624
	CS4	0.866				2.479
PWOM	PWOM1	0.877	0.913	0.939	0.793	2.651
	PWOM2	0.910				3.380
	PWOM3	0.909				3.293
	PWOM4	0.864				2.394

Regarding collinearity, all VIF values were below the critical value of 5.00, suggesting that collinearity did not pose a substantive issue in the model. Overall, these findings indicate that the measurement model achieved satisfactory levels of reliability and validity. Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT)(Hair et al., 2019). As shown in Table 4, all HTMT values were below the recommended threshold of 0.90, supporting satisfactory discriminant validity (Hair et al., 2022).

Table 4. Discriminant Validity: Heterotrait-monotrait ratio (HTMT)

	AI	BT	CE	CS	PWOM
AI					
BT	0.598				
CE	0.569	0.864			
CS	0.691	0.747	0.673		
PWOM	0.521	0.752	0.839	0.597	

Figure 2 shows that AI positively influences Brand Trust, Customer Engagement, and PWOM, while Brand Trust strengthens Customer Engagement, Customer Satisfaction, and PWOM. The model explains 29.5% of Brand Trust, 60.5% of Customer Engagement, 46.4% of Customer Satisfaction, and 46.8% of PWOM. The model has the strongest

explanatory power for Customer Engagement (60.5%), indicating relatively good explanatory capability.

Figure 2. Results of the Research Model

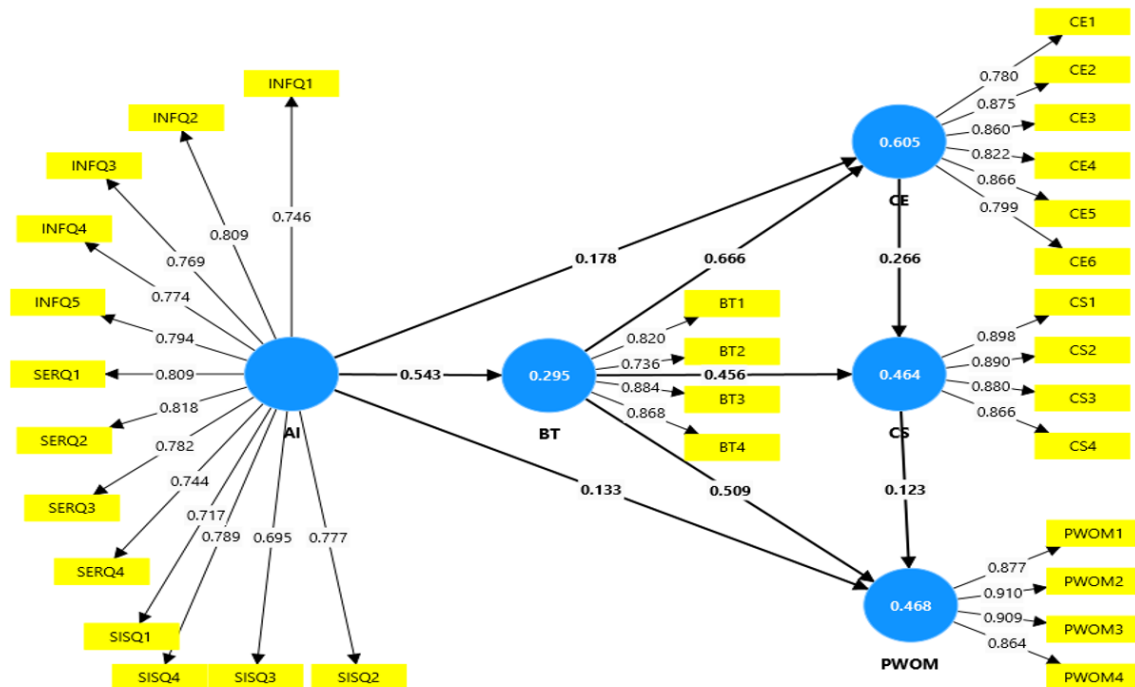


Table 5 shows that seven of the eight hypotheses were supported, while the effect of Customer Satisfaction on Positive Word-of-Mouth (PWOM) was not significant. AI Capability positively influenced Brand Trust, Customer Engagement, and PWOM, indicating that AI-enabled banking capability is associated with both relational and behavioral customer outcomes (Alagarsamy & Mehrolia, 2023; Ameen et al., 2021; Nguyen et al., 2021). Brand Trust also positively affected Customer Engagement, Customer Satisfaction, and PWOM, highlighting its important role in AI-enabled banking relationships (Ameen et al., 2021; Kumar & Pansari, 2016; Riedel et al., 2022). Customer Engagement significantly improved Customer Satisfaction, consistent with research on chatbot and AI-enabled service experiences (Alnaser et al., 2023; Hari & Iyer, 2021). However, Customer Satisfaction did not significantly affect PWOM, suggesting that satisfaction with AI-enabled banking services does not necessarily lead customers to recommend the bank. This supports the view that satisfaction and PWOM are distinct customer outcomes (Yun & Park, 2022). Although customer experience, satisfaction, and word-of-mouth are related, satisfaction alone may not explain subsequent behavioral intentions (Manyanga et al., 2022). In contrast, Brand Trust significantly influenced PWOM, confirming its stronger role in customer advocacy (Khan & Fatma, 2023). Thus, satisfied customers may become advocates only when satisfaction is supported by strong relational trust.

Table 5. Hypotheses Testing Results

H	Path	Original sample (O)	STDEV	T-Test	P- values	Decision
H1	AI -> BT	0.536	0.042	12.848	0.000	Supported
H2	AI -> CE	0.173	0.039	4.464	0.000	Supported
H3	AI -> PWOM	0.134	0.052	2.557	0.011	Supported
H4	BT -> CE	0.670	0.036	18.665	0.000	Supported
H5	BT -> CS	0.456	0.062	7.398	0.000	Supported
H6	BT -> PWOM	0.509	0.063	8.057	0.000	Supported
H7	CE -> CS	0.266	0.061	4.336	0.000	Supported
H8	CS -> PWOM	0.122	0.070	1.748	0.081	Not Supported

Table 6. Indirect effects

Path	Original sample	STDEV	T statistics	P values	Decision
AI -> BT -> CE	0.251	0.028	13.085	0.000	Supported
AI -> BT -> CE -> CS	0.096	0.024	4.083	0.000	Supported
AI -> BT -> CE -> CS -> PWOM	0.018	0.009	1.964	0.050	Supported
AI -> BT -> CS	0.172	0.043	5.814	0.000	Supported
AI -> BT -> CS -> PWOM	0.047	0.017	2.794	0.005	Supported
AI -> BT -> PWOM	0.203	0.037	7.909	0.000	Supported
AI -> CE -> CS	0.047	0.018	2.633	0.008	Supported
AI -> CE -> CS -> PWOM	0.009	0.006	1.502	0.092	Not Supported
BT -> CE -> CS	0.123	0.041	4.372	0.000	Supported
BT -> CE -> CS -> PWOM	0.034	0.016	2.043	0.041	Supported
BT -> CS -> PWOM	0.086	0.028	3.050	0.002	Supported
CE -> CS -> PWOM	0.050	0.026	1.975	0.048	Supported

Table 6 shows that most indirect effects were statistically significant, indicating that AI capability influenced customer outcomes through relational and behavioral pathways. A key pathway involved Brand Trust and Customer Engagement, suggesting that AI-enabled banking services can shape customer outcomes through service interactions (Alagarsamy & Mehroliya, 2023; Ameen et al., 2021; Chi & Hoang Vu, 2023). Brand Trust mediated the effects of AI Capability on Customer Satisfaction and Positive Word-of-Mouth (PWOM), highlighting trust as an important mechanism in customer responses (Riedel et al., 2022). Customer Engagement also contributed to Customer Satisfaction, indicating that active participation in AI-enabled banking supports positive service evaluations (Kumar & Pansari, 2016). However, the indirect path from AI Capability through Customer Engagement and Customer Satisfaction to PWOM was

not significant. Thus, engagement and satisfaction alone may not generate customer advocacy. Overall, Brand Trust is a key mechanism linking AI Capability to PWOM, while Customer Engagement and Customer Satisfaction play supporting roles. This finding aligns with research on AI chatbots, satisfaction, and word-of-mouth (Yun & Park, 2022) and the distinct role of customer advocacy (Sweeney et al., 2020).

CONCLUSION

This study concludes that AI Capability is significantly associated with Brand Trust, Customer Engagement, and Positive Word-of-Mouth (PWOM) in banking. Brand Trust is also significantly associated with Customer Engagement, Customer Satisfaction, and PWOM, highlighting its important role in AI-enabled banking relationships. The indirect effects show that AI Capability is associated with customer outcomes through trust, engagement, and satisfaction. However, the pathway through Customer Engagement and Customer Satisfaction does not significantly lead to PWOM. Thus, customer advocacy cannot be explained by satisfaction alone; relational factors, particularly Brand Trust, are important in generating positive customer responses.

The study contributes to the literature by extending research on AI-enabled banking beyond technology adoption and satisfaction to customer advocacy. The findings suggest that AI capabilities and relational factors, especially Brand Trust and Customer Engagement, jointly shape customer responses. Therefore, banks should improve AI functionality while strengthening reliability, responsiveness, information quality, transparency, and trust-building mechanisms. These efforts can increase customer confidence and engagement with AI-enabled services and encourage customers to recommend the bank.

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